REAL PROPERTY MARKET RESPONSES TO COASTAL FLOODING

by

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ABSTRACT OF THE DISSERTATION

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The high development pressure in coastal areas overlaps with significant natural hazards, such as storm surge related to flooding caused by hurricanes. Because of this, coastal zone management (CZM) becomes more important. Through CZM programs, the federal government has assisted state governments in improving local coastal planning and management. Studies in the implementation and practice of CZM in the United States include: protection of beaches, estuaries; and redevelopment of urban ports and waterfronts. The Federal Emergency Management Agency (FEMA) has developed land use regulations and technical guidelines as part of the coastal management efforts. Another important program to protect real property owners from severe flood damages on their properties is the National Flood Insurance Program (NFIP).

Therefore, this dissertation investigates the effects of coastal flooding on the dynamics of real property markets. Within the dynamics of real property markets, stakeholders respond to flooding differently based on their roles and interests. Real property market stakeholders' adaptive behavior in response to coastal flooding is the interest of this dissertation.

The complexity of these socio-economic phenomena interacting with ecological phenomena requires research methodologies that are able to analyze both at the aggregate level and at the micro level. Thus, this dissertation employs spatial hedonic regression pricing models that have been used traditionally in property appraisals, and agent-based modeling (ABM) that has recently gotten into attention among researchers as a tool to explore behaviors and emergences. By using a case study of real estate markets in Monmouth County, New Jersey, this dissertation investigates how these markets respond to coastal flooding caused by Hurricane Sandy that made landfall on October 30, 2012.

The resulting hedonic regression analyses find that flood risks are capitalized in real property prices. FEMA floodplain maps are found to inform the prices as suggested in lower prices among floodplain properties than similar properties located outside the floodplain. The findings also suggest that flooding affects real properties based on tenureship. Flooding has more impacts on owner-occupied properties than absentee-owner properties. In an analysis of the flood insurance market, the findings suggest that communities are not well-prepared for flooding, particularly coastal flooding caused by Hurricane Sandy. The ABM modeling outputs explore the non-marginal changes in property prices, which include the stakeholders' flood adaptation behaviors and the emergence of urban disinvestment and population decline caused by the capitalization of flood risks into real property prices.

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I am dedicating this dissertation to my parents for believing in me that I would finish what I started. To my sister, who continuously inspires me with her diligence in what she does.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ABM	Agent-based model
ACS	American Community Survey
AIC	Akaike Info Criterion
APPAM	The Association for Public Policy Analysis
CAMA	Computer Assisted Mass-Appraisal
CHI	Community Hardship Index
CRS	Community Rating System
CZM	Coastal Zone Management
DD	Difference-in-differences
DRA	Disaster Relief Act of 1974
FEMA	Federal Emergency Management Agency
FIRM	Flood Insurance Rate Map
GIS	Geographic Information System
GSE	Government-sponsored enterprise
HFIAA	Homeowner Flood Insurance Affordability Act of 2014
HHI	Household Hardship Index
HMGP	Hazard Mitigation Grant Program
IPCC	Intergovernmental Panel on Climate Change
NFIP	National Flood Insurance Program
NGO	Non-governmental agency
NJDCA	The New Jersey Department of Community Affairs
NJDEP	The New Jersey Department of Environmental Protection
NJDOT	The New Jersey Department of Transportation
NJGIN	The New Jersey Geographic Information Network
NJMLS	New Jersey Multiple Listing Service
NOAA	The National Oceanic Atmospheric Administration
NOS	National Ocean Service
OPRSS	Open Public Records Search System
QGIS	Previously called Quantum GIS
SBA	Small Business Administration
SFHA	Special Flood Hazard Area

Chapter 1

Introduction

1.1. Background

Problems facing urban areas are becoming more complex. Some of these problems, including housing shortages, economic recession, ecological degradation, and aging amenities, continue to challenge urban planners to adjust their paradigms and practices. This dissertation addresses one of these many problems, namely the understanding of the impacts of coastal storms on urban communities. The dissertation begins with an overview of planning theories that have been used to address urban issues, the rationales and use of some analytical planning tools including hedonic regression models and agent-based models (ABM), and ends with how these tools can be useful to inform planning and policy-making processes.

This chapter discusses the background context, characteristics and evolution of planning paradigms leading to the influence of an economic rationale in those planning paradigms—such as spatial economics and economics of aggregation—to explain the vulnerabilities in coastal urban areas, particularly real property markets. Finally, this chapter lays out the five hypotheses and research questions and the structure of the rest of the dissertation.

1.2. Introduction

Hurricane Sandy hit the U.S. eastern coastal cities on October 29 – November 2, 2012. The water levels along the U.S. east coast from Florida northward to Maine rose immediately as the storm surged inland. The highest storm surges occurred in the states of New Jersey, New York, and Connecticut. Damaging waves and storm surges hit some locations around the coast of central and northern New Jersey and Staten Island. The highest storm surge measured by tide gauge operated by National Ocean Service (NOS) in New York was 12.65 feet above normal tide levels at Kings Point on the western end of Long Island Sound while a gauge in New Jersey measured at 8.57 feet above normal tide levels at the northern end of Sandy Hook in the Gateway National Recreation Area and a gauge in Connecticut measured 9.83 feet above normal tide levels at Bridgeport.

I started my doctoral study at Rutgers in just a month before Sandy. I experienced and saw the devastating impact the hurricane caused. My three weeks without power and cold night sleep and shower were not comparable to the distress of people living at the shore, who faced a direct hit by the storm. Hurricane Sandy killed 147 people, 72 people in the United States alone. Sandy caused tens of billions of US dollars lost financially and displaced numbers of households with thousands of buildings damaged or destroyed. At least 55,000 homes were damaged or destroyed in New Jersey (Blake, et.al., 2013). About 8.5 million customers were without power for weeks or even months in some areas. Sandy caused an estimate of 30 to 50 billion dollars in damage in the United States.

In the aftermath, government institutions at the federal, state, and municipal levels launched recovery efforts and planning to mitigate future risks related to storm and floods. On January 28, 2013, the Federal Emergency Management Agency (FEMA) released updated flood insurance maps for New York and New Jersey that had previously operated under the 1986 maps. The updated flood zone covered larger areas and twice as many structures as in the previous maps. Communities also worked hand in hand with relief organizations and neighboring communities in rebuilding and making their cities more resilient to future storm events. Rutgers University provided shelters for its faculty, staff, and students, who were impacted by the storm. The Reformed Church of Highland Park, NJ, was one of the many that hosted relief volunteers visiting from other places around the country. Harry Pangemanan, one of the volunteers, said about his encounter with the affected community in Belmar, NJ, “When we have the family go back to the house, that’s always the most joyful part,” … “Especially the kids, ‘I miss my room, my room is back,’”.[1] Pangemanan’s statement has inspired me to carry out this dissertation research in Monmouth County, New Jersey.

While Hurricane Sandy devastated the lives of people living in the New Jersey coastal areas, the real property markets was not likely to suffer long-term impacts from the storm. At that time, economists from the Federal Reserve Bank of New York said that real property market, typically, experience a temporary dip in prices and activities after storm events and followed by a rebound quickly. Possible longer-term effects are on the insurance costs and stricter construction standards. As a result, the cost of living may become higher and the demand for coastal properties may become lower. This strongly relates to the stakeholders’ economic decisions. For example, homebuyers may choose to rent as opposed to buy homes. Homeowners may shift their investment in installing flood protection measures. Insurers increase the premiums charged to policy-holders. This dissertation, thus, tries to examine the effects of flooding on the valuation of homes and the stakeholders’ decisions in response to climate events, and how these have been

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[1] Yi, Karen. 2016. Nearly-deported man helps Sandy victims rebuild. Asbury Park Press, part of the USA Today Network. http://www.app.com/story/news/local/culture/2016/08/25/jersey-shore-rebuilding-homes/88516004/. Accessed on Dec 2016

translated into policies and practices, such in the formation of the National Flood Insurance Program (NFIP).

1.3. Goals and Research Hypotheses

In the dissertation, I examine the relationships between coastal flooding and responses by multiple stakeholders participating in real property markets such as homebuyers and owners, developers, private insurers, and policy makers. As noted earlier, increasing pressure of development in the coastal areas and significant impacts of coastal storms may move the focus of climate resilience to the community level. In order to devise predictions of real estate market behavior in response to coastal storms, policymakers need to understand the empirical links between the roles and behaviors of real property market actors, communities, and physical characteristics of storm-impacted areas.

To understand the impacts of adaptation behaviors on real estate market dynamics towards coastal flooding, I explore the historical trend of real property market transactions and behaviors of actors in a specific real property market. Therefore, the emergence of phenomena such as capitalization of flood risk in home prices and flood insurance purchases can be observed. In particular, this dissertation seeks to test the following hypotheses:

5.1. Real estate markets fully capitalize flood risk into the prices of properties.

This part investigates whether home prices reflect flood risk in the aftermath of flood events. The transactions between homebuyers and homesellers later shape the dynamics of the real property market. In order to investigate further, I seek answers to the following subsidiary questions:

1) What market factors do homebuyer consider in buying properties?
2) What uncertainties can be identified in the local real property markets?

5.2. Homebuyers do not properly account for flood risk when deciding to buy properties in flood prone areas.

This part considers a flood risk reduction effort at the level of the individual homebuyer. Homebuyers often overlook flood risk in purchasing their desired homes. Other reasons maybe because they are willing to pay the damage costs caused by flood events. To support the hypothesis, I have the following questions:

1) What are the time horizons used by people in perceiving flood risk?
2) Does perception of flood risk vary by wealth?
3) How do homebuyers perceive flood risk differently than home renters?

5.3. Flood events exacerbate prior community trends toward gentrification or urban disinvestment.

Ongoing interplay within the climate change issue is now developing into new forms of interaction between people, political elites, and planners. Therefore, it is important to study the governance patterns formed through the interaction of these stakeholders to determine the success of the resilience strategies as well as the effects on the real property market. As governments need to re-strategize investment priorities toward disaster recovery, social equity issues become prevalent in the communities in the aftermath. Residents often question government's decisions in rebuilding their communities. This part answers the following questions:

1) Are there changes in social, economic, or demographic characteristics of communities in the aftermath of large flood events?
2) Do people shift their investment strategies from purchasing homes to renting?
3) Do developers' investment strategies often not reflect the need of existing residents, who just suffered damages from a disaster?

5.4. National Flood Insurance Program (NFIP) has the unanticipated consequence of moral hazard to encourage development in flood risk areas.

Since its inception, NFIP has had both positive impacts and negative impacts. NFIP has provided assistance to insurers and burdened the federal budgets with debts. NFIP has also been known to encourage development on the floodplains. More exploration on this topic is covered by investigating the following questions:

1) What are the characteristics of flood insurance policy-holders?
2) Has the NFIP enabled new development in floodplains?
3) Do people purchase flood insurance due to a "flooding effect" or "information effect"?

5.5. Community-level flood risk reduction efforts vary across municipalities and it influences stakeholders' perception on future risks and the actual impact of flooding.

This part discusses how well communities perform in coping with flood risk. One widely used measure is the Community Rating System (CRS). CRS is a voluntary program for NFIP participating communities. Communities rated using this system receive discounted premiums as incentives to go beyond the minimum floodplain management requirements by developing extra flood protection measures. CRS and other similar programs are used to inform homeowners about flood risk. The following questions are examined to support this study:

1) Are community-level risk reduction efforts still rare?
2) Do CRS and other similar programs explain perceived flood risks?
3) Do trust-levels among stakeholders in the community leads to high transaction costs associated with collaborative action?

1.4. Research Design

Pre-dissertation Methods

I made several visits to the New Jersey shore and spoke with homeowners, a real estate agent, a FEMA officer, a Tax assessor, and relief effort volunteers. The research presented here is related to other projects conducted in Monmouth County, New Jersey, during the Sandy recovery period, the outcomes of the dissertation could work as a model for future similar studies. During the process, I also had several informal conversations with one of the early key people in the formation of NFIP at the Association for Public Policy Analysis (APPAM) Conference in 2015.

Dissertation Methods

In order to achieve the dissertation goals, I employ hedonic regression models and an agent-based model (ABM). Hedonic models have been widely used in real property valuation. ABM is used to capture stakeholder behavior interacting in a real property market. Chapter 2 describes these two approaches in greater detail.

I also adopt a case study method in order to cross-examine similarities and differences of coastal flooding across real property markets, flood insurance markets, and ultimately adaptation initiatives. In the process of preparing the case study, I took a realist approach by identifying important issues that surround the flood risk management (Byrne & Ragin, 2013). Flood risk management includes two major components, one is the natural condition of flooding and another is its interaction with stakeholder behavior. As a case study, I selected Monmouth County in New Jersey due to the devastation it experienced during Sandy and in the aftermath. Monmouth County was one of the many counties in New Jersey that had the hardest hit during Hurricane Sandy and in the aftermath in 2012. I consider Monmouth County as a case study for the analyses on real property market and flood insurance market (see Chapter 3 and 4). In the analyses for stakeholders' behaviors using the proposed ABM, I selected two municipalities within Monmouth County. The two municipalities have unique features that are worth comparing. Physical characteristics include the proportion of flood-prone areas and both were impacted by Hurricane Sandy. Another characteristic is the demography, which includes population and population growth rate. I also account for socio-economic characteristics such as median household income and unemployment, poverty index, number of housing units and types, property values, median gross rents, and housing tenureship.

1.5. Thesis Contributions

There are three major contributions of the dissertation: (1) Characterizing stakeholders' decision-making; (2) Policy recommendations; (3) Methodologies and planning tools. This dissertation informs stakeholders' decisions. It provides an analysis of flood-related fees and explanation of flood adaptation options to homebuyers and homeowners. The analysis leads to a better flood-risk awareness to them. Developers will also find the detailed analysis on real property valuation useful, particularly as it shows how flooding impacts real property market. The proposed ABM model also enables local planning officials to explore stakeholders' flood adaptation behavioral patterns. The model is also useful as a policy simulation and communication tool. The analysis on flood insurance market is also useful for insurers to anticipate "surprises" when they need to pay for claims requested by insurance policyholders, who are affected by flooding. Insurers may also use the analysis to estimate flood insurance premiums charged to the policyholders.

This dissertation also offers guidance on how to restructure current policies surrounding flood management, particularly in setting priorities that address the affordability of flood insurance premiums and other costs related to reducing flood risks. It also provides a model of clear and timely dissemination of information about flooding and the related risks to the corresponding stakeholders. Moreover, the discussion on resilience to coastal flooding and its economics does not have to be siloed onto discrete topics, which range from science of sea level rise to governance, but the integration of these topics. It diagnoses aspects of environmental phenomena affecting the aspects of the real property market. The dynamics of real property markets discussed in this dissertation include spatial and environmental conditions of coastal regions, as well as stakeholder behavior. This dissertation offers an analytical approach to investigate real property and flood insurance markets. It presents hedonic models on property sales and flood insurance purchase (and claims) to help in identifying the determinants and to provide a larger picture of the real property market dynamics. Also, the coupling of hedonic models and ABM allows us to explore individual and collective decisions that, eventually, determine the success of resilience efforts.

1.6. Thesis Structure

This dissertation is organized in four further chapters. Chapter 2 reviews theoretical literatures on real estate market dynamics from resilience planning, economics of space, and economics of aggregation. It also discusses the empirical studies and computational studies of real property market and flood insurance market dynamics from the aspects of determinants, behaviors, and case studies in Monmouth County, New Jersey.

Chapter 3, "The Impact of Hurricane Sandy on Real Property Prices", describes homebuyers' perceptions of flood risks. In it I examine diverse attributes that influence property prices in Monmouth County, New Jersey from the period 2001-2015. Location of properties (e.g. floodplain or not), housing tenureship (e.g. owner-occupied or absentee-owner), and flood risk discount duration are some of the attributes that are discussed in the chapter. I use the flooding caused by storm-surges associated with Hurricane Sandy in 2012 to test whether a large flood event informs flood risk perception and, hence, capitalizes property prices.

Chapter 4, "Flood Insurance in Monmouth County, New Jersey", describes factors that influence flood insurance purchase in Monmouth County, NJ, during the period 2001-2015. Some factors that are worth investigating are properties' demographics of buyers, locations of properties, housing tenureship, and recent flood events. In this chapter, I explore flood insurance market penetration at the municipal and property levels in Monmouth County. Flood insurance penetration and factors that influence the market are compared across municipalities. I also examine structural and neighborhood factors of individual real properties that influence flood insurance purchases.

Chapter 5, “Modeling Coastal Real Property Market Dynamics using An Agent Based Modeling (ABM) approach,” describes the complexity of housing markets in greater detail by exploring nonmarginal changes affecting the real property market, such as stakeholder behavior in response to coastal flooding. I bring an integrated model of spatial hedonic model of housing market and an ABM model. I employ a traditional hedonic model to find coefficient values of real property’s attributes affecting sales price and an ABM approach to explore flooding adaptive behavior of stakeholders (i.e. homeowner, homebuyer, homeseller, local government, real estate broker, and flood insurance provider). The last chapter, “Conclusions,” describes the employability of these various analyses as tools to inform policy-making processes. I also summarize findings and identify potential future endeavors.

Table 1.1: A summary of dissertation structure

Hypotheses	Description	Chapter
H1	Real property markets fully capitalize flood risk into the prices of properties.	3
H2	Homebuyers do not properly account for flood risk when deciding to buy properties in flood-prone areas	3,5
H3	Flooding exacerbates prior community trends toward gentrification or urban disinvestment.	3,5
H4	National Flood Insurance Program (NFIP) has an unanticipated consequence of moral hazard that encourages development in the areas with high flood risk.	4
H5	Community-level flood risk reduction efforts vary across municipalities and it influences stakeholders’ perception on future risks and the actual impact of flooding.	5

Chapter 2

Literature Review

2.1. Introduction

This dissertation research relies on the relevant theories and empirical studies of real property markets in coastal cities. Resilience in planning combines the two previous planning paradigms, namely rational comprehensive planning and communicative planning, in addressing issues facing our cities that require both immediate and long-term actions (Holling, 1973). Cities around the world are driven to maintain economic driven through, mainly, entrepreneurship, land, and real property. A set of economic literature has confirmed it (Solow, 1999). As cities around the world, particularly ones with a close proximity to the coastline, become more vulnerable to flooding, resilience has tightened its relationship with urban economic development. Since flooding can significantly impact the quality of life, people start to put it into consideration when purchasing properties in addition to the commonly-used indicators such as structural, neighborhood, and school qualities. These buyers interact with property sellers in a market, hence, shaping the whole market dynamics that is reflected in market prices. Thereby, multiple stakeholders can use the price to inform layers of economic decisions. For example, developers use prices to set appropriate cost of any new development. Appraisers and assessors use it to estimate properties with similar characteristics in the area. Local planning and government officials may use it to inform economic-related policies. Flooding does not only inform property prices, it also affects people’s awareness on flood risk in terms of purchasing flood insurance. Previous studies have suggested an increase in flood insurance purchase immediately after flooding despite whether the flooding has directly or indirectly impacted them.

2.2. Resilience in Planning

Urban areas are home for many small and large communities. Some are resilient to crises such as flooding, but others are not. These problems facing our communities and the responses put the neoliberal approach in planning to a test. The neoliberal planning approach here refers to the involvement of planning in the production of self-regulating market economies, within which a group of private interests are allowed substantial control over life socially and politically in order to maximize profit. In the past two decades, we saw changes in neoliberal policies and governance that led to changes in the institutionalization of governance, especially in the context of planning for cities (Brenner, 2009; Feiock, 2009; Fuller and Geddes, 2008; Gunder, 2010; Eraydin, 2011). Under a neoliberal economy, communities share responsibilities and risks with individual residents and organizations. A trend in public private partnerships emerges to include stakeholders from various backgrounds from policy makers, municipal official members, planners, real property developers, non-governmental agencies (NGOs), neighborhood committees, and city residents. These stakeholders drive the growth of their cities through businesses and real property development. It is not rare that the accelerating growth in economies comes with the decline of other important aspects of the community such as the equity and environmental aspects (Campbell 1992a, 1996).

Thereby, the intervention by the government and public funding became more prevalent. Yet, there is no evidence that the intervention is a response to the failure of market system. Evaluations of cities' policies, plans, and programs have resulted in proposals to include more adaptive and capacity-reorganization components. One of the many proposals is the introduction of resilience concepts to planning practice. Resilience does not describe ecology and socio-economy as two separate systems (Holling, 1973; Berkes and Folke, 1998; Berkes et al., 2003). According to Holling (1973), "resilience determines the persistence of relationships within a system and is a measure of ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist." In this definition, resilience brings what is out-of-balance back to the original condition (Davoudi, 2012). Leichenko (2011) puts on emphasis on a 'diversity' of approaches as one of the key tenets within the resilience concept.

Table 2.1. illustrates how resilience in planning practice combines the two previous major planning paradigms, namely rational comprehensive planning (1950s-1980s) and communicative planning (1980s-present). According to Eraydin (2013), resilience planning differs from the previous two planning paradigms in its focus on the means to reduce the risks embedded within indefinite ends. Moreover, resilience planning evaluates issues by relying on inputs from both individual experts and stakeholder consensus. Table 2.1. also describes that the resulting evaluation is used to come up with plans that would not require only immediate action but also a long-term solution. This highlights one of the major concerns in planning such that a balance interaction between natural processes and socio-economic processes can be achieved through an understanding of planning concepts. Planning requires a transdisciplinary perspective on spatial and temporal processes occurring in cities as suggested in the examples above. In the next two sections, two perspectives from economics discipline will be discussed. The

first is in regards to land, on which most of the processes take place, and stakeholders, by whom the manipulation of the processes are completed.

Table 2.1: A comparison of three planning paradigms

	Rational comprehensive planning	**Communicative planning**	**Resilience planning**
Rationality	Instrumental	Communicative	Integrative
Evaluation	Efficiency	Consensus-based values	Resilience attributes
Actors	Individual experts	Individuals in focus group	Interdisciplinary groups with technical expertise
Time Range	Medium to long term	Short term	Systems approach, immediate, and long-term
Concern	Problem solving	Consensus decision	Prioritize issues raised under the constraints of instrumental rationality act
Result	Technical-driven decisions	Collective values-driven decision	Flexible solutions

Source: Adopted from Eraydin (2013)

2.3. The Economics of Space (e.g. Real Property Market)

The economy, as a complex system (Arthur and Durlauf et al. 1997), interacts with other systems via scales of processes. Scale has many dimensions, including the spatial, temporal, quantitative, or analytical, to measure and study a phenomenon (Chave and Levin, 2004; Rotmans, and Rothman, 2003; Manson, 2008). In contrast, process has unique attributes and produces different outcomes across different scales (Axelrod, 1997). For example, environmental conditions often influence behaviors of a flock of birds, or a swarm of bees or a colony of ants. The makeup of the surrounding environment can even make individual behaviors to form a collective behavior (Janson and Middendorf, 2005; Couzin, 2009). In economics, the study of space or land highlights the problem of linking ecological-economic systems. The spatial dimension becomes extremely important because of heterogeneity attributed to the land that influences processes in both economic and natural systems. This is especially true in the study of real estate market and land market, where people make economic decisions based on spatially explicit attributes (Randal and Castle, 1985; Hubacek and van den Bergh, 2006).

Early regional economic studies had a limited consideration of spatial heterogeneity, such as in the following studies: travel costs in general equilibrium models, distance to central business district, economic agglomeration (Isard, 1972; Fujita Hu, 2001), location decisions (Alonso, 1964), and environmental economics (Wu, 2001). Externalities like utilization of the neighboring land and existing governmental policies have been concerns in real property and land markets studies. The development of spatial econometric models toward a more explicit modeling is one of the responses by real property market researchers (Chapter 3, 4 and 5).

2.4. The Economics of Aggregation

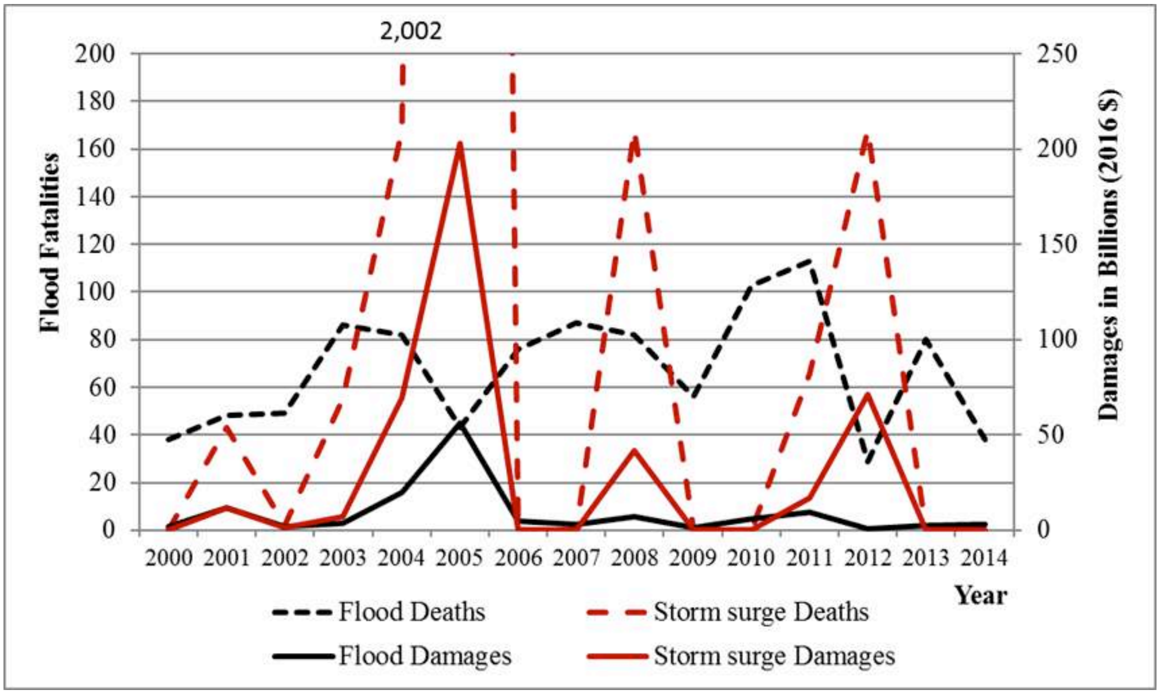
Another characteristic of complex systems is the diversity of components and interactions among them, producing feedbacks between different levels of the components (Levin, 2003). In economic studies, individual components and behaviors are often studied separately from the rest of natural systems (i.e. land). This is probably the reason we have separate studies of microeconomics, where individual economic decisions and behaviors are closely observed; and macroeconomics, in which inflation rate, prices, and unemployment are some of the main subjects. The transition between a micro-scale and a macro-scale requires a model of aggregation to formalize a large system bounded within limited variables.

One way of aggregating microscale to macroscale in economics is to suggest the existence of a “representative agent”, such that the behavior model of an economic agent is extended to represent the behavior of the whole group of agents (Varian, 1992). A representative agent is rational and maximizes profit in its interaction with others. The interaction that results is an equilibrium price, which occurs in a market economy. Another model of aggregation is known as Agent-Based Modeling (ABM) (Tesfatsion, 2001). ABM acknowledges the heterogeneity of interacting agents taking roles in real-world economic systems, which a model of “representative agent” cannot explain. The dynamic interaction occurring within an ABM model does not necessarily end in equilibrium. In the research implementation, ABM uses a simulation modeling approach in addition to mathematical or other conventional analytical tools. This dissertation evolves from using a conventional spatial hedonic model to ABM in understanding economic stakeholder behavior in coastal real estate markets (Chapter 2 and 5).

2.5. Coastal Flooding and Economic Responses

The topical issue of climate change is also an inherently complex system that has developed through various applications of sub-topics and approaches. Flood risk threatening coastal communities is one of them. The high development pressure in the coastal regions overlaps with significant natural hazards. Hurricanes and coastal storms are main causes for natural hazards affecting coastal areas. Hazards include high winds, tidal surges, beach erosion, bluff failure, and coastal flooding. While storm wave erosion and offshore earthquake-driven tsunamis are threats to the U.S. Pacific Coast, Tropical storms and hurricanes are the major coastal storm problem on the Atlantic and Gulf Coasts, South Florida, and southeast Texas. The resulting floods worsen the damages in these vulnerable areas. More than 75 percent of declared Federal disasters have been accounted to flooding.

Figure 2.1 illustrates that floods have caused almost $8 billion in property damage and have killed 90 people on average annually. Storm-surge-related flooding caused by tropical cyclones had even worse impacts during the period as suggested by the red lines and red dotted-lines in Figure 1.1. In the past twenty years, Hurricane Katrina, a Category 3 tropical storm that impacted New Orleans in 2005, had the largest impact in flood damages. The storm resulted in the failure of parts of the levee system along with $153.9 billion in damages and 1,833 deaths. Hurricane Irene and Hurricane Sandy were the major storms that hit the U.S. northeastern seaboard in the past five years. While Hurricane Irene made a landfall on New Jersey shore in 2011, Hurricane Sandy hit the same regions in 2012 and caused $68.3 of storm surge damages and 159 people were killed.



Data source: National Oceanic and Atmospheric Administration (NOAA)

Figure 2.1: Flood fatalities and flood damages for the period 2000-2014

The high urbanization and more apparent impacts of climate change make coastal zone management more important. Through the Coastal Zone Management (CZM) program, the federal government has assisted state governments in improving coastal planning and management[2]. The implementation and practice of CZM in the United States includes: protection of beaches, dunes, bluffs, and rocky shores (Bernd-Cohen and Gordon, 1998); protection of estuaries and coastal wetlands (Goods et al., 1998); and redevelopment of urban ports and waterfronts (Goodwin et al., 1997). The Federal Emergency Management Agency (FEMA) has developed land use regulations and technical guidelines and the National Flood Insurance Program (NFIP) for states and localities, which each will be discussed in this dissertation. The success and failure of any

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[2] The U.S. Congress passed the Coastal Zone Management Act (CZMA) in 1972. Since then the act is administered by NOAA. https://coast.noaa.gov/czm/act/

coastal management efforts really depends on regulations in protecting sensitive areas, better design, restoration, watershed management of land use and stormwater runoff, and other protection mechanisms.

Coastal communities may have implemented different strategies for climate resilience, yet the composition of stakeholders, which operate these strategies, and their political practices were found to be similar (Schechtman, 2016; Psuty & Ofiara, 2002; Psuty & Silveira, 2007). The success rate of such strategies depends on their willingness to have successful programs. These stakeholders include local government as the governing institution, planners as the knowledge experts, and people as the local sources. Henceforth, this study aims to explore how people, as economic agents with their heterogeneity, perceive flood risk, respond to flood events, and how their decisions affect the regional economic outcome, such as the real property market and flood insurance market.

Flood risk in coastal areas that include direct potential economic damage, is often capitalized in real estate prices. Low awareness of flood risk biases economic decisions in a real estate market, and leads to an increase of risk in flood-prone areas and inefficient real estate market outcomes. Multiple factors influence flood risk awareness of both the individual and community such as dissemination of flood risk information, flood insurance, and building codes. These factors drive policy formation to increase flood risk awareness and, thus, affect economic behaviors of coastal real estate markets (Chapter 3 and 5).

2.6. The National Flood Insurance Program (NFIP)

One important factor that influences flood risk awareness is flood insurance.

Since its establishment by the National Flood Insurance Act of 1968, NFIP has provided flood insurance coverage to communities that choose to adopt minimum floodplain management policies. FEMA produces Flood Insurance Rate Maps (FIRMs)[3] that show the flood elevation throughout the participating counties in order to determine each household's risk and associated premium. Three basic goals of NFIP include: to better indemnify individuals for flood losses through insurance; to reduce flood damages through management and regulation; and to reduce federal expenditures for disaster assistance and flood control (FEMA, 2002). NFIP has been a concern since 2005 when floods of claims came from Hurricanes Katrina and Rita that eventually left NFIP in great debt. The debt to the treasury exceeds $19 billion.

The NFIP has 40 percent of all policies in force nationwide are in Florida and close to 70 percent of all policies-in-force in just five states: Florida, Texas, Louisiana, California, and New Jersey (Michel-Kerjan and Kousky, 2010). Forty years after its inception, the NFIP has grown significantly. It covers $1.23 trillion of assets. As of December 2010, there were 5.65 million NFIP policies in force nationwide, which generated $3.35 billion in premiums with average annual premium per policy $593 nationwide.

Studies show that purchasing flood insurance can lead to a behavioral change by individuals in response to a policy or program. This makes them less careful about their actions than potential losses would suggest, changing the likelihood of suffering those losses (Zahran et. al., 2008). A particular question regarding NFIP is whether the

[3] Flood Insurance Rate Map (FIRM) that is used to determine whether a property is in the floodplain; the flood insurance zone that applies to the property; the approximate base flood elevation (BFE) at the site.

program has the unexpected consequence of encouraging more buildings in the areas that are most vulnerable to flood risk (Boulware, 2009). Browne and Halek (2009) suggests that, in Florida counties, NFIP participation was increased for both single family and multifamily residential development, however, no evidence has yet been found that prompted development from the program is any more or less more severe in high flood risk areas. Economic aspects might provide another set of reasons as to why many homeowners make flood insurance purchases and keep them for a period of time. While a proportion of the homeowners live on a fixed income, others depend on some form of government assistance on a monthly basis.

Beliefs about flood risk also influence people's decisions about flood control. It is prevalent for people not to rely on information on probabilities in making their decisions. Therefore, it may not be very helpful for making decisions in regards of taking protection measures by telling people "you are in a 100-year return period floodplain" (see Appendix A.1 for more explanation on the FEMA flood zones). In a survey conducted in 1978 it was found that only 12 percent or fewer NFIP participating responders was aware of the building codes or land use regulations to mitigate flood damage; and only 1 percent was aware of insurance mechanisms to manage risk from flood events (Kunreuther et. al., 1978). Effective risk communication becomes important, or else flood insurance and other flood control programs may give a false sense of protection with respect to suffering damage from floods. Another explanation is that people ignore risks whose subjective odds are below a certain threshold (McClelland, Schulze, and Coursey, 1993).

Low flood risk awareness among homeowners leads to low participation and short tenure of flood insurance. There have been proposals to reform NFIP. Collaboration among institutions is one aspect to be improved. Michel-Kerjan (2012) recommends for Congress and FEMA to work more closely with banks and Government-sponsored enterprise (GSEs) such as Fannie Mae and Freddie Mac, to ensure a higher compliance rate with the mandatory purchase requirement. Multi-year contracts on flood insurance can be designed and implemented as to ensure properties coverage given transfer ownership of properties.

In regards to the affordability of flood insurance premium pricing, incentives, discounts, and other financial assistance have already been made available through both public and private organizations. Recent large flood events resulted in the elimination of certain rates in premium discounts. Another explanation for the increasing premiums is the adoption of new flood maps and the elimination of grandfathering under Biggert-Waters Flood Insurance Reform Act. Kousky and Kunreuther (2013) proposes a voucher program that can be coupled with a mitigation loan program. A subsidized disaster loan from the Small Business Administration (SBA) and Hazard Mitigation Grant Program (FEMA-HMGP) funds are other options made available for rebuilding. These recommendations on the improvement of the flood insurance mechanism are mainly for people to invest more in risk reduction measures and for banks to have safer mortgages. Chapter 3 discusses the flood insurance market at both community and property levels.

2.7. Methods

Hedonic regression model is frequently used to estimate real property prices. It was first used for estimating automobiles' price index (Court, 1939). The concept was later expanded by Lancaster (1966) for various applications such as housing and financial assets. Hedonic analyses comprised of multiple components, such as buyer-supplier's interaction (Rosen 1974), market segments (Bajic, 1985), structural attributes (Raslanas et al., 2006), location attributes (Malpezzi, 2002; Keskin, 2008), neighborhood attributes (Ayse Can 1990), and natural phenomena (Beron et.al., 1997; FEMA, 2001; Bin and Polasky, 2004). Sirmans, Macpherson, and Zietz (2005) detailed a summary of common characteristics used in previously published hedonic models. Traditional OLS estimates can often produce biased and inconsistent results since they do not consider spatial dependence and spatial heterogeneity, especially when the model includes a locational component (LeSage, 1999; Mueller and Loomis, 2008). This is because a traditional regression model often violates the Gauss-Markov assumptions. Gauss-Markov assumes the independent variables are fixed in sampling. Spatial heterogeneity also violates the Gauss-Markov assumption, in a way, that a linear relationship with constant variance exists across the observations. This requires alternative estimation procedures to fit the model every time variance changes. The hedonic regression models, thus, add a neighborhood effect by considering the presence of spatial dependence, in which observations depend on one another based on their unique locations, and spatial heterogeneity, where these observations vary in relationships over space.

Chapter 3 and 4 of this dissertation discuss the spatial regression models in comparison with OLS models and other models, based on the research questions being asked. A Difference-in-differences model (DD model) is also used to measure the differential effect of Hurricane Sandy on the real property market. Another method that is adopted in the dissertation is a Fixed Effects (FE) model that is used to control unobserved independent variables that are not random and do not change across ross-sectional data.

Another method that is used in the dissertation is the ABM models. ABM enables a bottom-up investigation of the dynamics of a real property market by acknowledging the microeconomic agents' decision making and spatial characteristics (Batty, Longley & Fotheringham, 1989). Microeconomic agents, including property buyers, property owners, and property sellers, have very distinct characteristics. The tendencies for these agents to socially influence and be influenced by each other are significant aspects contributing to the housing market dynamics. Moreover, the real property market is susceptible to external factors such as other economic indicators and non-economic indicators in the region. Housing bubble and climate change effects on housing markets are some of the examples that are often found in the discussion.

ABM has been used to explore human social phenomena where complex processes and resulting emergence become the focus of the study. Some of the known applications of ABM or other computational approaches include trade, migration, decision-making, military strategy, human-environment interaction, disease propagation, and population dynamics. ABM enables researchers to create computer models of reality, depicting the actual phenomena. There are three basic components of ABM models: agents, an environment or space, and rules. Agents are representations of individuals in the real world economic system. In a coastal real property market, for example, agents involved in the model are homeowners, homesellers, homebuyers, local government, developers, and home insurers (Parker, et al., 2012; and Magliocca, 2012). The space in ABM world represents the environmental conditions in the system. In the example of housing market dynamics, the ABM space could be constructed based on the spatial map of land parcels (or, block lots, tracts, and municipal boundaries), amenities, land topography, and sea levels. While space is separate from agents in ABM, rules governing the environment, and the agents' behavior dominates all processes occurring in simulations. The simulated agents behave, interact with other agents, and move within the space based on rules applied to them. The construction of these rules is ideally supported by data collected from the actual world. These rules define the kind of social networks among agents similar to the actual human networks. Axtell and Epstein, in their book, *Complex Adaptive Systems*, described in detail about the collective phenomena of these agents (Epstein & Axtell, 1996, Chapter 5). Besides agents' social networks, another concept that is adopted by ABM is object-oriented programming, or OOP. OOP is commonly found in modern programming languages such as JAVA and C++. These programming languages treat both agents and environmental space as objects that hold both data and procedures. The agent's attributes are data such as sex, age, and income; and the agent's procedures are the agent's rules of behavior such as buying, selling, and foreclosing house. For this dissertation, ABM is implemented within a NetLogo and JAVA programming environment (Wilensky, 1999).

Chapter 5 of this dissertation extends an earlier ABM model that I and my co-authors have published, that was created based on a conceptual model of flooding affecting coastal communities in Highlands, NJ (Chandra-Putra, Zhang, and Andrews 2015). Unlike the previously published model, referred to as 'Handi's 2015 model' throughout the dissertation, this dissertation proposes a more integrated ABM model. As indicated in the literature, ABM models have been used for applications on the flooding impacts on property markets in Hungary (Brouwers and Boman, 2012), North Germany (Sobiech, 2013), United Kingdom (Dubbelboer et al., 2017), and in the US (McNamara and Keeler, 2013; Filatova, 2009; Filatova & Bin, 2013; Filatova, 2015).

2.8. Hurricane Sandy Impacts and Responses: The Case of Monmouth County, NJ

This dissertation looks into changes in the dynamics of real property market in New Jersey coastal communities prior to and after Hurricane Sandy in 2012. The analysis then requires selecting real property markets that were impacted by Sandy and shared similar characteristics. Monmouth County was hit the hardest by Hurricane Sandy, making it appropriate as a case study (Hoopes Halpin 2013). According to a report authored by Hoopes Halpin in 2013, Monmouth County scored 84 on a scale from 1 (no damage) to 100 (extensive damage) in the Community Hardship Index (CHI)[4] among the other twenty-one counties in New Jersey. CHI is a measure to compare the damages caused by Sandy across New Jersey counties and municipalities. Monmouth County suffered the most overall in terms of electricity outages, real property damages, residents in shelters and gasoline shortages. In terms of Household Hardship Index (HHI)[5], Monmouth County ranked third with a score of 65 on a scale of 1 (least hardship) to 100 (greatest hardship). Hudson County had the highest score (=69) among NJ's 21 counties (Hoopes Halpin 2013). According to a report released by the Federal Emergency Management Agency (FEMA), the county has $172 million of flood damage from the hurricane.

Geographically, Monmouth County is located in the central part of New Jersey.

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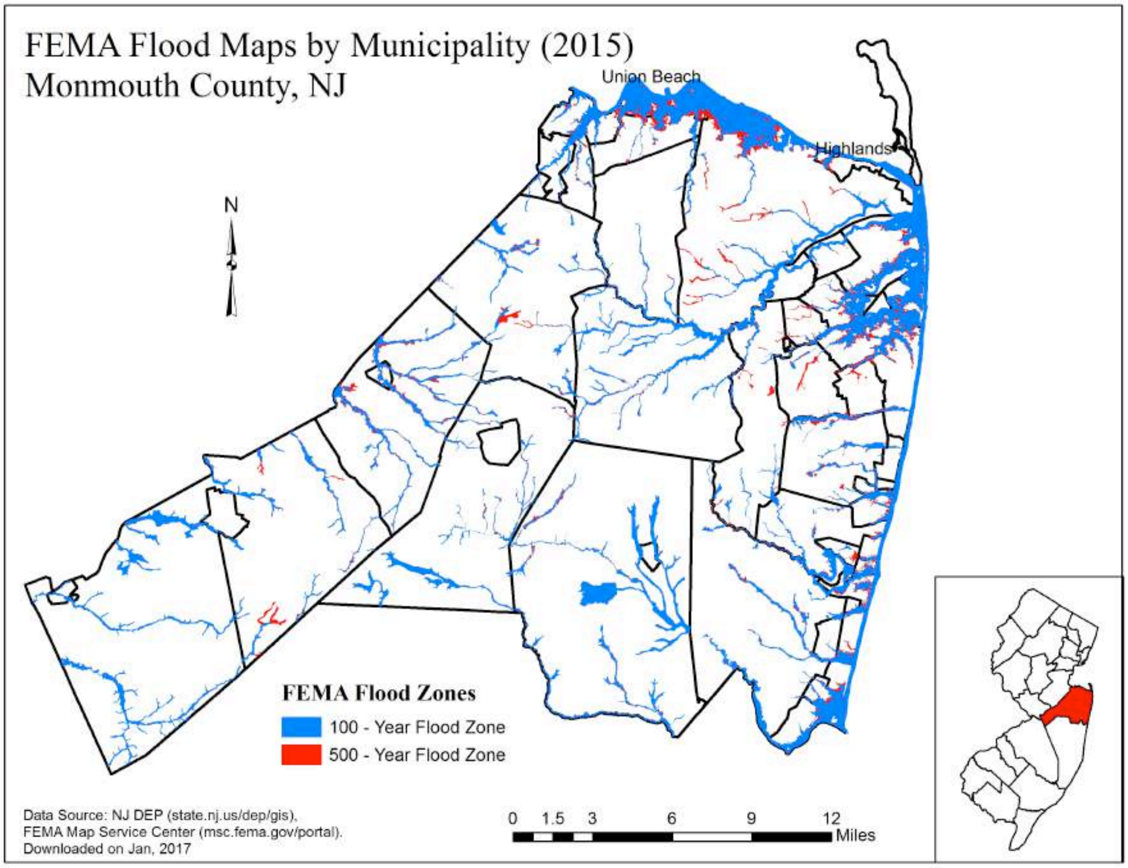
[4] Community Hardship Index (CHI) is a compilation of different types of indicators into one measure to reveal which counties or towns were most and least impacted by Hurricane Sandy.

[5] Household Hardship Index (HHI) measures the scope, severity, and resilience of households with income below the ALICE threshold, which measures the cost of basic household necessities.

The county is bordered by the Atlantic Ocean to the east, Mercer County to the west, Middlesex County to the north, Ocean County to the south, and Burlington County to the southwest. It covers 665 square miles, with a population of 629,384 (U.S. Census Bureau 2010). Several major highways span in Monmouth County, including the Garden State Parkway, New Jersey Turnpike, Interstate 195, and State Roads 9, 18, 34, 35, 36, and 70. Several rail lines and bus lines also pass through the County, such as the New Jersey Transit North Jersey Coast Line.

Monmouth County has experienced flooding that was mainly caused by tropical storms, extratropical cyclones (known as northeasters) and severe thunderstorms. Near the Atlantic Ocean, Raritan Bay, Navesink River, Sandy Hook Bay, Shark River, and Shrewsbury River, flooding is often caused by high tidal surge and wave activity caused by coastal storms like hurricanes. Monmouth County has a significantly large low-lying areas that are vulnerable to flooding and flood-related damage resulted from the periodic flooding caused by overflow from streams and lakes (see Figure 2.1).



Data source: FEMA floodplain maps

Figure 2.2: Floodplain in Monmouth County, NJ (2015)

One of the most vulnerable communities in Monmouth County is Union Beach Borough. It is in the floodplain surrounded by swamps and marshland. According to the Borough's Department of Emergency Management Agency, the Borough was uninhabitable when Hurricane Sandy made landfall on October 29, 2012. In this dissertation, Union Beach and Highlands are also considered for further analysis by using ABM. Chapter 5 of this dissertation discusses in detail the rationale of selecting the two municipalities and ABM as an appropriate method for the analyses.

To reduce flood risk, the New Jersey Department of Environmental Protection and Division of Land Use Regulation regulate the development and use of land within floodplains and the floodway. Some communities within Monmouth County have developed river cleanup programs to clear debris near bridges and sewers to prevent backwater flooding during storm events. Several structural flood protection measures (e.g., dams) are installed on Conines Mill Pond and Indian Run in Allentown Borough. Other small dams are on Swimming River in Middletown Township, on Tinton Avenue in Tinton Falls Borough. Small dikes protect Ocean Township from tidal surges into inland areas on Whale Pond Brook and Poplar Brook. Wave management measures were placed near roads and other infrastructure in Wall Township. Monmouth County does not have levee type structures[6].

2.9. Conclusions

The impacts of coastal flooding caused by storm surges from Hurricane Sandy on the New Jersey's communities were devastating. Yet, nobody really knew the actual impacts on real property markets at that time as stated by the economists from the Federal Reserve Bank of New York. Cities have taken into account resilience in their master plans. In planning theory, resilience concerns not only long-term economic growth of cities but also actions to address immediate threats, such as flooding or terrorist attack. Resilience collects inputs both from individual expertise and stakeholders' consensus. Resilience in cities has taken a transdisciplinary approach, in which an integration among relevant approaches is often required. For example, flooding impacts on a real property market, which is used as a case study for the dissertation, discusses resilience in relation

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[6] Section D.2.10.3.4.1 of the Draft Atlantic Ocean and Gulf of Mexico Coastal Guidelines update and the current FEMA policy state that in instances where levees cannot meet the requirement for recognition by the NFIP, the levees shall be "removed" from the analysis.

with environmental aspects (e.g. FEMA flood zones), economic aspects (e.g. flood risk capitalizing in property prices); behavioral aspects (e.g. stakeholders' flood-adaptation strategies).

Most empirical studies on the coastal flooding impact on the real property market focuses on the aggregate variables related to the property, such as structural, neighborhood, locational, and flood-related attributes as suggested in most of the macro-level analyses based on hedonic models. The effects of each variable on the price are calculated and compared at the property level. However, the behavioral aspect occurring within the real property market dynamics is often missing. Integrating with computational models, such as ABM enables us to see a clearer picture of how past flooding experiences have affected the awareness of property owners on future flood risks, hence, have impacted the flood insurance purchase and property price.

Chapter 3

The Impact of Hurricane Sandy on Real Property Prices

Abstract

This chapter seeks to test the first hypothesis, “Homebuyers do not properly account for flood risk when deciding to buy properties in flood prone areas” and the fourth hypothesis, “Flood events exacerbate prior community trends toward gentrification or urban disinvestment”. By using a hedonic property pricing approach, this chapter provides an analysis of property price estimators such as structural characteristics, neighborhood characteristics, distance to nearest locations of certain amenities, as well as flood-risk related attributes such as flood zones and distance to nearest water bodies. Additionally, this chapter provides an analysis by using FEMA floodplain maps and inundation maps to determine the effect of Hurricane Sandy on property price. Moreover, the analysis also uses information on housing tenureship to see the differential effects on real property prices.

3.1. Introduction

Coastal regions provide a unique venue for studies on land and real property markets. Dynamic interactions between social and environmental landscapes are easily observed in these regions. While social activities include demographic growth, economic development, and social mobility; land has its roles as soil or mineral resources, terrain for ecosystems functions, an administrative unit, and real estate (Randall and Castle 1985). The intensity in the interaction increases as the complexity increases, such as in the large climate event. A single event, Hurricane Sandy, for example, produces various explanations to different subject-outputs. Climate scientists have linked Hurricane Sandy to other extreme climate events (Trenberth, 2015), an ecological perspective has brought insights on the resulting environmental impacts of Hurricane Sandy on soil and water contamination that lead to public health issues (Manuel, 2013). The economic perspective, which examines the allocation of land and resources in the marketplace, has reported the devastating economic losses on land and real properties. There are several reasons that cause the increasing flood damage to properties. The first is because of the increasing frequency and intensity of larger climate events, such as hurricanes. There were 23 major storms recorded between 2000 and 2015, while it was only 17 and 15 storms with similar scale, recorded in 1980s and 1990s, respectively (NOAA, 2016). Another reason is the increasing urbanization in flood-prone areas (Kunreuther and Michel Kerjan, 2007; Freeman, 2003; IPCC, 2007). The increasing real property value has increased the economic losses of flood events. According to Burby (2001), there were over six million buildings located in the 100-year floodplain. This chapter, thus, presents an empirical analysis of the capitalization of flood risk in the price of real estate.

Studies show that properties located in the floodplain have lower market values than properties with similar characteristics that are located outside floodplain (Shilling et al., 1985; Bin and Polasky, 2004; Bin and Kruse, 2006; Bin et al., 2008; Kousky, 2010; Atreya, 2013). Many homeowners are unaware of the flood risk attributed to their homes, especially to those that have a close proximity to the water. Consequently, they often do not expect a great loss from a flood event. A recent flood event is often a wake-up call to homeowners. In New Jersey, the increasing flood insurance premiums and cuts to premium subsidies have made homeowners realize the high flooding costs. Related studies indicate that these costs are capitalized in housing prices (Bin et al. 2008; Daniel et al., 2009; Kousky, 2010; Bin and Landry, 2012; Atreya et al., 2013; and Atreya and Czajkowski, 2014). In addition to the characteristics of whether the property's location is within the floodplain and its distance to nearest coastline, other flood risk indicators include elevation (McKenzie and Levendis, 2010; Kousky, 2010; and Atreya et al., 2013) and variance of flood risk return periods (Atreya and Czajkowski, 2014).

Large flood events like Hurricane Sandy also shift property investment patterns. Homeowners, whose homes were flooded during Sandy or in the 100-year floodplain, purchase flood insurance policies for a short-term period after the flooding. The investments in property alterations and other flood control mechanisms are also higher after Sandy made a landfall than prior Sandy. People reconsider buying houses and choose to rent, instead, as to avoid paying flood-risk related costs. The socio-economic decisions of people adapting to future flooding and/or other natural disasters with similar scale affect the market prices of properties. Whether this investment shift is due to the recent flooding or not remains the focus of the paper. Properties located in the floodplain tend to show a trend of a temporary drop in market value following a flood event (Bin and Polasky, 2004). Kousky (2010) points out that real properties located in the 500-year floodplain decrease in prices more than prices of properties located in the100-year floodplain. Bin and Landry (2012) also shows that properties in the 100-year floodplain are discounted in price, immediately after the flooding. Atreya (2013) captures an information effect and inundation effect with her findings that an increase in the price discount for 100-year floodplain properties is significant, while the price discount for

500-year floodplain properties is not significant. The price discount in the three studies is found to be short-term with an estimate of 3-4 years. All three studies but Atreya's (2013), consider specific damages to properties. However, the discount for floodplain properties present after flooding is consistent with the damages that resulted from the flood. This also provides evidence that flooding informs peoples' perceptions on flood risk.

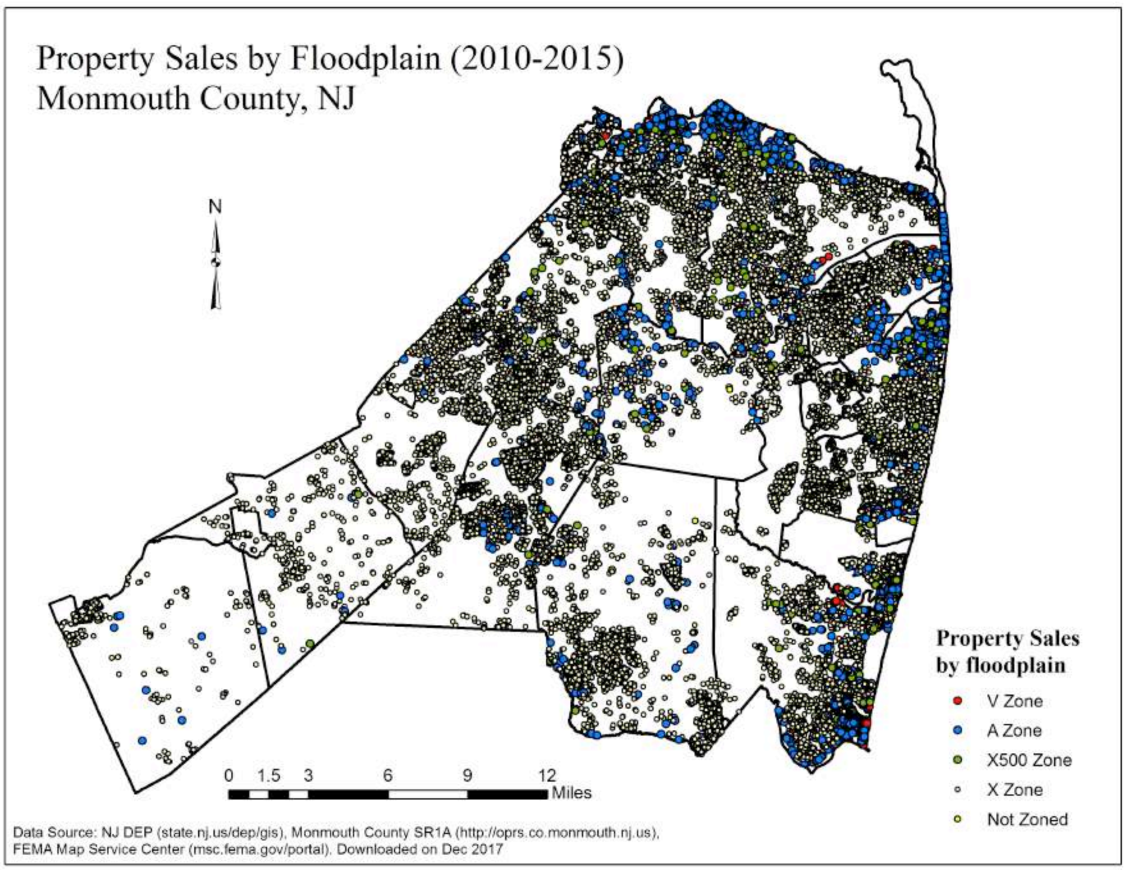
This study also explores other variables that would potentially affect flood risk, thus, real property values. These variables include flood reduction program, community awareness, and housing tenureship, influence flood risk. Community Rating System (CRS) is one of the many indicators to identify community awareness and commitment to flood risk reduction. CRS is a voluntary incentive program under the National Flood Insurance Program (NFIP) that encourages flood reduction activities. CRS communities are eligible for up to a 45 percent discount on their flood insurance premiums. Similar to previous studies, this study hypothesizes that a large flood event such as Hurricane Sandy, increases flood risk discounts. This study also considers categories within the coastal real property market; a sub-market of rental properties is one of them.

In testing each hypothesis mentioned above, this study presents hedonic models of the real property market in Monmouth County, New Jersey by examining determinants of flood risk and Hurricane Sandy in a more detailed case study. The resulting analysis tells us that Hurricane Sandy in 2012 contributes to the property price discount immediately in the aftermath. Similar to previous studies, properties located within the 100-year floodplain are found to be lower in prices than their counterparts located outside the floodplain. Rental properties and owner-occupied properties located within 0.75 miles from the nearest coastline contribute positively to the prices at a significant level. The remainder of the chapter discusses topics as follows: Section 3.2 provides an overview of the Monmouth County, New Jersey, study area and data used in the hedonic property pricing analysis; Section 3.3 lays out the methods to address the study's hypotheses and followed by discussion on results that are presented in Section 3.4. Section 3.5 concludes with potential policy research and an introduction to Chapter 4, which discusses the patterns of flood insurance purchase in greater detail.

3.2. Monmouth County Property Market and Data

This study uses Monmouth County for a case study. Monmouth County was one of the many New Jersey's counties that were hard hit by Hurricane Sandy (Hoopes Halpin, 2013). Sales data for all properties in Monmouth County (SR-1As) is provided by the Monmouth County Tax Board office through the Monmouth County Open Public Records Search System (Monmouth County OPRSS). The Tax Board office also provided two additional data that are used jointly with the SR-1A data. One is data on current owners (or, assessment list), called MOD-IV data. Another is Computer-Assisted Mass-Appraisal (CAMA) data that provides more information on property structure and floorplan. After adjusting the sales prices to 2016 prices using a consumer index for housing, some outliers on sale prices are present. The analysis does not include properties with extremely large in square footage and very expensive property sales. Foreclosed properties are also not included since these sales tend to skew the results of statistical analysis. Arguably speaking, the sales also do not really represent the average homebuyers' purchasing decisions. These properties are excluded from the analysis based on 95% of the data fall within two standard deviations of the mean. By considering only the most recent sale of the residential properties, which is coded with a numerical value 2 in the MOD-IV data, there are 33,984 property sales for the analysis between 2010 and 2015. Among these properties, 17 percent are absentee-owner properties.

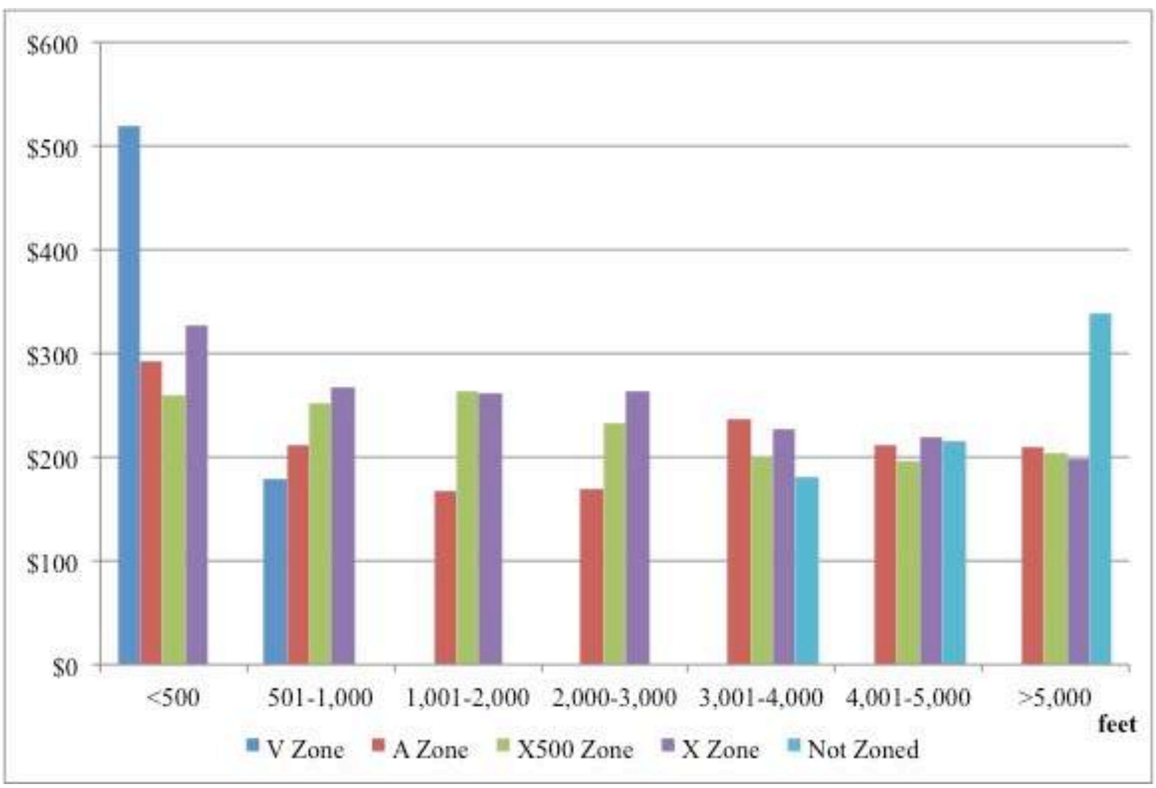
Figure 3.1 illustrates the location of these sales by FEMA designated flood zones of 100-year floodplain (V zone—with wave action and A zone), 500-year floodplain (X500 zone), and outside 100-year and 500-year floodplains (X zone). Please see Appendix 1 to read more about FEMA flood zones.



Data source: NJDEP, MOD IV, FEMA Map Service Center

Figure 3.1: Real property sales and associated flood zones in Monmouth County, NJ

There were 54 home sales in the V/VE, 3774 sales A/AE/AO zones and 30,872 sales per year in the X/X500 zones during the period between 2010 and 2015. By calculating the Euclidean distance to the nearest coastline, it is expected that prices per square foot for homes in the V and A zones are higher on average than prices per square foot for homes outside these flood zones. Figure 3.2 summarizes that as the distance to the nearest coastline increases, both homes sales and sales price per square foot within each flood zone decrease. The aggregate variables of distance from a property parcel centroid to the nearest coastlines are Euclidian distances calculated using the linear (N*kx3) distance matrix analysis. The same method is used for all nearest distance calculations in the dissertation. While the method is not appropriate for some types of analyses, it compensates the accuracy for the computing efficiency due to the large datasets. Using network distance may fit better for nearest distances to types of transit hubs such as distances to the nearest bus stops and train stations.



Data source: FEMA floodplain maps, Monmouth County SR1A, NJ DEP

Figure 3.2: Average sales price per-square foot (in US$) by flood zones over various

distances to coast (in feet)

Hedonic models (Court, 1939; Lancaster, 1966) have been used to estimate a combination of factors influencing the total value of a heterogeneous good, such as real property. In the real property market application, the interaction between suppliers and consumers is one of the many important factors (Rosen, 1974). Other important factors, including structural variables, location variables, neighborhood variables are also considered in estimating real property value. These real property attributes can bring both negative and positive effects on real property value. Ayse Can (1990) argues the importance of “neighborhood dynamics in urban house prices” with his standardized neighborhood quality score. He develops the score based on nine neighborhood characteristics: the percentage of nonwhite population, percentage of unemployed population, median household income, percentage of families under the poverty level, ratio of owner-occupied units to absentee-owner property units, percentage of vacant units, percentage of housing units with complete plumbing, percentage of housing units built before 1939, and per capita crime to property. In 1985, Validimir Bajic identified the existence of sub-housing markets. Differences in attribute prices should be taken into account across different market segments. In the residential property market, hedonic models have been including more quantitative attributes like floor area, lot size, number of stories, age, etc., and qualitative attributes like condition, neighborhood quality, architecture, etc. (Raslanas, 2006). These attributes are commonly viewed as interior that includes physical structure, neighborhood quality, market conditions, and housing policies, and exterior that includes physical, social, cultural elements and access to job centers and urban amenities (Keskin, 2008). Sirman, Macpherson, and Zietz (2005) analyzed 125 previously published hedonic property pricing models.

This study includes the following structural characteristics in estimating the hedonic property price function: building square footage, number of stories, building age at the time of sale, type of foundation with concrete slab = 1and 0 = otherwise (concrete, concrete block, pier, pipe), exterior wall type with brick = 1 and 0 = otherwise (concrete, metal, wood), a dummy variable for the structural condition with 1 = excellent and 0 = otherwise (poor, average, fair, good, very good), dummy variables for availability of the following features = 1 and 0 = otherwise: attic, basement, air conditioning, forced hot air, Jacuzzi, fireplace, dormer, deck, dock, pool, porch, garage, patio, and first story shed. The neighborhood characteristics, such as the median household income and the percent of non-white population is determined at the census block group using 2010 and 2013 American Community Survey (ACS) and census tract using 2010 decennial census data. In addition to the distance to the nearest coastline, the continuous variables for each property are calculated based on distances from a property to the nearest bus stop, rail station, school, police station, and contaminated sites are also included in the estimation. Most towns in Monmouth County participate in NFIP. Properties in these towns that were built after 1974, were required to elevate the structures above the base flood elevation, PostFIRM = 1 and 0 = otherwise.

Table 3.1 describes the summary of statistics of the variables used in the analysis. The average sales price is $451,009 (SALEPRICE) with a typical age about 48 years old (BLDGAGE) and 1,983 square feet in size (SQFT). Most properties are owner-occupied as suggested by OWNEROCCUPIED = 0.8065. The average distance to the nearest coastline is 15,820 feet (CoastDIST) and 70 percent of homes are located within 500 feet of the coast (COAST500=1). Some other flood-related variables are also accounted in the models. There are 11.156 percent of the homes sold located within the 100-year floodplain (FLDZONEV and FLDZONEA). Also, 47 percent of the homes were built after FEMA had mapped the flood risk in the area or referred to as post-FIRM structures (POSTFIRM). 1.27 percent of sales were made within a month after Hurricane Sandy made landfall as suggested by the variable ASANDY1M. More discussion on the variables and data sources can be found in Appendix A.

Table 3.1 Description and the summary statistics of the variables

	Min	**Max**	**Median**	**Mean**	**Std. Dev.**
SALEPRICE (usd)	1,069.92	8,421,311	353,073.8	451,009.1	422,086.9
BLACKPCT (%)	0	89.021	0	3.459	7.119
COLLEGEPCT (%)	13.682	100	70.075	68.738	14.451
RENTTOTAL (usd)	0	1300	63	109.36	127.28
MEDINCOME (usd)	18,300	250,001	92,708	97,205.76	38,177.36
HHSIZETOTAL	1.21	5.07	2.73	2.6909	0.5594
VACANTPCT (%)	0	63.974	4.882	8.413	11.335
COAST (=1)	0	1	0	0.4748	0.4994
OWNEROCCUPIED (=1)	0	1	1	0.8065	0.3951
SEWER (=1)	0	1	1	0.9223	0.2677
WATER (=1)	0	1	1	0.8799	0.3251
GAS (=1)	0	1	0	0.0658	0.2479
SEPTIC (=1)	0	1	0	0.0497	0.2173
BLDGAGE (years)	1	379	46	48.72	28.16
SQFT (square feet)	0	23,205	1788	1,982.88	1,069.2
CONDITION (=1)	0	1	0	0.00415	0.06427

ROOMS	0	24	6	5.722	2.003
HEIGHT	1	3.5	2	1.6839	0.4896
FCONCBLK (=1)	0	1	1	0.6753	0.4683
FCONCSLB (=1)	0	1	0	0.2116	0.4084
FCONCPOUR (=1)	0	1	0	0.0794	0.2704
FPIERPIL (=1)	0	1	0	0.00117	0.03422
FSTNBRK (=1)	0	1	0	0.03068	0.17246
hasAC (=1)	0	1	1	0.793	0.4051
hasFIREPLACE (=1)	0	1	0	0.1245	0.3302
hasDORMER (=1)	0	1	1	0.8856	0.3183
hasDECK (=1)	0	1	0	0.4456	0.497
hasDOCK (=1)	0	1	0	0.00573	0.0755
hasPOOL (=1)	0	1	0	0.02616	0.15961
hasSHED1STY (=1)	0	1	0	0.2356	0.4244
hasBRICK (=1)	0	1	0	0.233	0.4228
POSTFIRM (=1)	0	1	0	0.4678	0.499
CoastDIST (feet)	3.5	80,311.4	6,309.1	15,819.8	18,538.5
StreamDIST (feet)	1.73	7,350.84	832.49	1,087.18	942.48
RailStDIST (feet)	267	145,208	12,989	24119	24,507
PoliceDIST (feet)	2.3	34,596.81	5,387.89	6,865.97	5,151.25
PollutDIST (feet)	7.87	14,337.55	2,225.92	2,727.28	1,880.99
SchoolDIST (feet)	96.91	20,345.13	2,459.17	3,030.66	2,255.18
FLDZONEA (=1)	0	1	0	0.1087	0.3113
FLDZONEV (=1)	0	1	0	0.00156	0.03941
FLDZONEX500 (=1)	0	1	0	0.03186	0.17564
FLDZONEX (=1)	0	1	1	0.8576	0.3495

COAST500 (=1)	0	1	0	0.0692	0.2538
COAST1000 (=1)	0	1	0	0.0738	0.2614
COAST2000 (=1)	0	1	0	0.1096	0.3124
COAST3000 (=1)	0	1	0	0.0803	0.2718
COAST4000 (=1)	0	1	0	0.0689	0.2534
COAST5000 (=1)	0	1	0	0.0521	0.2222
ASANDY (=1)	0	1	1	0.6168	0.4862
ASANDY1M (=1)	0	1	0	0.0127	0.112
ASANDY2M (=1)	0	1	0	0.0123	0.11023
ASANDY3M (=1)	0	1	0	0.01109	0.10473
ASANDY4M (=1)	0	1	0	0.01458	0.11986
ASANDY5M (=1)	0	1	0	0.00827	0.09056
INUNDATED (=1)	0	1	0	0.0514	0.2209

Data sources: Monmouth County MOD IV, SR1A sales records, NJDEP, FEMA

3.3. Method

This study, systematically, compares three models of Ordinary Least Squares (OLS), Spatial Lag, and Spatial Error. While the OLS model has been traditionally used in previous studies for valuing property prices, the spatial lag and spatial error models make the estimation by considering spatial dependency in the observations. A difference-in-differences (DD) framework is also used to compare prices of floodplain properties with non-floodplain properties before and immediately after flooding.

This study examines the impacts of coastal flood risk on property values in Monmouth County, NJ. By using the actual property transaction data explained in the previous section, hedonic property pricing models are used to break down the values of properties' characteristics in estimating sales price of a property, **P**. In the analysis, the property sales price is log transformed in order to minimize heteroskedasticity and because the sales data is positively skewed with a long right side tail (Wooldridge, 2003). Independent variables are grouped into three categories: structural characteristics, **S**; neighborhood characteristics, **N**; natural log of location characteristics, **L**; and flood zones, **F**. The model also incorporates housing tenureship, **T**, to capture the effects of different sub-markets (i.e. owner-occupied and absentee-owner properties). In order to examine how these characteristics affect the hedonic price, the model can be arranged in four ways. The first two models are to check the effects of housing tenureship and how it will likely differ conditional upon floodplain.

$$\ln(\mathbf{P}) = \beta_0 + \beta_1\mathbf{S} + \beta_2\mathbf{N} + \beta_3 \ln(\mathbf{L}) + \beta_4\mathbf{F} + \beta_5\mathbf{T} + \mathbf{e} \quad (1)$$

$$\ln(\mathbf{P}) = \beta_0 + \beta_1\mathbf{S} + \beta_2\mathbf{N} + \beta_3 \ln(\mathbf{L}) + \beta_4\mathbf{F} + \beta_5\mathbf{T} + \beta_6(\mathbf{F} * \mathbf{T}) + \mathbf{e} \quad (2)$$

In order to estimate the effect of Hurricane Sandy on sales price, a difference-in-differences (DD) model (Equation 3) is compared with the model of prior Sandy, which accounts for sales before Sandy hit the region. Studies of the effects of natural disasters on real property values can be traced back to the late 1990s. In 1997, Beron, Murdoch, Thayer, and Vijverberg studied the effects of 1989 Loma Prieta earthquake. They found a larger price discount after the disaster. Similar studies were also conducted on flooding case by using the DD model (Bin and Polasky, 2004; Kousky, 2010; Bin and Landry, 2012; Atreya, 2013). Previous studies compared the difference in effects of flooding between floodplain properties, the treatment group, and non-floodplain properties, the control group. In the model for this dissertation, the two independent variables of flood zones (**F**) and sales after Hurricane Sandy (**Sandy**=1) and their interaction term (**F** *

Sandy) provide a coefficient that tells how flooding resulted from Hurricane Sandy affected the sales prices of floodplain properties sold after the flooding. A sub-model is created for only those home sales pre-Sandy from January 2010 to August 2012.

$$\ln(\mathbf{P}) = \beta_0 + \beta_1\mathbf{S} + \beta_2\mathbf{N} + \beta_3 \ln(\mathbf{L}) + \beta_4\mathbf{F} + \beta_5\mathbf{T} + \beta_6(\mathbf{F} * \mathbf{T}) + \beta_7 \mathbf{Sandy} + \beta_8(\mathbf{F} * \mathbf{Sandy}) + \beta_8(\mathbf{T} * \mathbf{Sandy}) + \mathbf{e} \qquad (3)$$

In the application to real property markets, hedonic pricing models also take into account spatial dependence since property values across space are possibly related (Can, 1990). Like previous studies in the literature, this study uses a measure of spatial autocorrelation to determine whether neighboring real properties have similar values. Hot spot analysis, cluster analysis, and Moran's I test are most common methods to identify the presence of spatial dependency (Anselin and Rey, 1991). Building a regression model with the unobserved spatial characteristics can be a challenge. Anselin (1988, 2005) developed two ways to add spatial dependence into a regression model. The first is a spatial lag model that focuses on spatial interactions of a dependent variable, sales price, by including a weighted average of its neighbors' prices that is called a spatially lagged dependent variable. A weighted average sales price of the property's neighbors is noted as **WP**. The spatial dependence coefficients, ρ and λ, are also estimated. Another way is to include spatially correlated errors, u, due to location-specific omitted variables and other unobservable characteristics. The spatial error regression considers the presence of unobservable characteristics related to the property location. In other words, the interest to correct for spatial dependence is because the structure of the spatial relationship remains unknown. Therefore, the new regression function looks as follows:

$$\ln(\mathbf{P}) = \lambda\mathbf{W}\ln(\mathbf{P}) + \beta_0 + \beta_1\mathbf{S} + \beta_2\mathbf{N} + \beta_3 \ln(\mathbf{L}) + \beta_4\mathbf{F} + \beta_5\mathbf{T} + \beta_6\mathbf{Sandy} + \rho\mathbf{W} + u \qquad (4)$$

There are two ways to construct the spatial weight matrix that is utilized to explain spatial relationship among observations. Contiguous weight matrix is based on shared borders and vertices. This is appropriate for polygon spatial data. Another method is a distance-based weight matrix, which measures the distance between parcels. Parcel data is geo-coded based on X-coordinate and Y-coordinate to calculate distance between observations. This study considers a distance-based weight matrix. Two data subsets are considered in the analysis. One represents owner-occupied properties and another represents all absentee-owner properties. By considering only properties that are sold after Hurricane Sandy, we see how the estimators are also different in their significance. Spatial weight matrices for the data sets are created within the GeoDa 1.6.7 9 (2015) environment. ArcGIS is used to calculate the Euclidian distance from each property to the nearest amenities (i.e. coastline, rail station, bus stop, school, police station, and school), which is not ideal for some of nearest distance calculations as suggested in the previous section.

3.4. Regression Results

Table 3.2 shows the regression results of two hedonic property pricing models as in equation (1) and in equation (2) with a sample size of 33,984 sales. The models estimate the effects of housing tenureship given various FEMA flood hazard zones. The two models control aggregate variables of 100-year floodplain (FLDZONVVE and FLDZONAAE) and 500-year floodplain (FP500) and having them interact with the variable that explains housing tenureship (OWNERSHIP).

Both models show that properties located in the high-risks area of A and AE zones (FLDZONAAE) have lower property prices than their counterparts that are outside floodplain. However, it is only in Model (1) that shows lower-risks area (FP500) has a negative effect on property price at 0.01 significance level. In model 2, where housing tenureship (OWNERSHIP) is at test, owner-occupied properties have higher prices than absentee-owner properties. All interactions between OWNEROCCUPIED and aggregate floodplain variables are found to significantly influence the property prices at 0.05 and 0.01 levels. However, it is only the interaction term of OWNEROCCUPIED and FP500 that negatively influence the prices, others are positive. Finally, the R-squared' values for Model 1 and Model 2 are 0.63 and 0.64, which indicate that the regression line approximate the real sales data points.

Table 3.2: Regression results using housing tenureship and the FEMA floodplain maps. Dependent variable is a log-transformed variable of sale price

	Model (1)	**Model (2)**
(Intercept)	1.18E+01***	1.16E+01***
	(8.59E-02)	(8.42E-02)
acs_pctcoll	7.81E-03***	7.83E-03***
	(2.54E-04)	(2.48E-04)
acs_renttotal	6.65E-05***	7.12E-05***
	(2.43E-05)	(2.38E-05)
acs_medincome	1.65E-06***	1.49E-06***
	(1.22E-07)	(1.19E-07)
acs_hhsizetotal	-3.42E-02***	-2.65E-02***
	(6.47E-03)	(6.34E-03)
acs_pctvacant	8.17E-03***	9.35E-03***
	(2.76E-04)	(2.72E-04)
acs_pctblack	-7.04E-03***	-6.79E-03***
	(3.79E-04)	(3.71E-04)
OWNEROCCUPIED		1.98E-01***
		(6.86E-03)
SEWER	-9.96E-02***	-1.01E-01***
	(1.29E-02)	(1.26E-02)
WATER	-2.67E-02**	-2.61E-02**

	(1.17E-02)	(1.14E-02)
GAS	8.39E-02***	1.00E-01***
	(1.13E-02)	(1.11E-02)
SEPTIC	8.59E-03	1.01E-02
	(1.34E-02)	(1.31E-02)
BLDGAGE	-1.95E-03***	-1.71E-03***
	(1.69E-04)	(1.65E-04)
SQFT	2.18E-04***	2.13E-04***
	(3.83E-06)	(3.75E-06)
CONDITION	3.28E-01***	3.69E-01***
	(3.77E-02)	(3.69E-02)
ROOMS	7.43E-02***	7.61E-02***
	(2.11E-03)	(2.06E-03)
HEIGHT	6.19E-02***	5.41E-02***
	(6.21E-03)	(6.08E-03)
FCONCBLK	6.79E-02	5.64E-02
	(5.53E-02)	(5.41E-02)
FCONCSLB	-7.06E-03	-2.09E-02
	(5.56E-02)	(5.45E-02)
FCONCPOUR	1.43E-01**	1.32E-01**
	(5.61E-02)	(5.49E-02)
FPIERPIL	2.43E-01***	1.89E-01**
	(8.95E-02)	(8.76E-02)
FSTNBRK	1.41E-01**	1.21E-01**
	(5.68E-02)	(5.56E-02)
hasAC	2.03E-01***	1.85E-01***
	(7.20E-03)	(7.06E-03)
hasFIREPLACE	6.18E-02***	6.07E-02***
	(7.92E-03)	(7.75E-03)
hasDORMER	-4.28E-02***	-4.01E-02***
	(7.85E-03)	(7.68E-03)
hasDECK	4.54E-02***	3.90E-02***
	(5.09E-03)	(4.98E-03)
hasDOCK	4.30E-01***	4.18E-01***
	(3.40E-02)	(3.33E-02)
hasPOOL	9.41E-02***	9.66E-02***
	(1.55E-02)	(1.52E-02)
hasSHED1STY	1.58E-02***	7.86E-03
	(5.80E-03)	(5.68E-03)
hasBRICK	1.75E-02***	1.42E-02**

	(6.03E-03)	(5.90E-03)
POSTFIRM	-4.46E-02***	-4.47E-02***
	(8.47E-03)	(8.28E-03)
LDSTREAM	-4.14E-03	-2.53E-04
	(2.94E-03)	(2.87E-03)
LDBUSSTO	1.05E-02***	8.26E-03***
	(2.82E-03)	(2.76E-03)
LDRAILST	-6.59E-02***	-6.22E-02***
	(2.96E-03)	(2.90E-03)
LDPOLICE	-3.25E-02***	-3.48E-02***
	(4.12E-03)	(4.03E-03)
LDPOLLUT	5.61E-02***	5.56E-02***
	(4.20E-03)	(4.11E-03)
LDSCHOOL	-2.85E-02***	-2.39E-02***
	(4.20E-03)	(4.11E-03)
FLDZONVVE	1.11E-01*	-8.09E-02
	(6.27E-02)	(9.97E-02)
FLDZONAAE	-2.44E-01***	-3.96E-01***
	(9.51E-03)	(1.55E-02)
FP500	-3.68E-02***	2.20E-02
	(1.42E-02)	(3.01E-02)
COAST500	2.16E-01***	2.20E-01***
	(1.27E-02)	(1.24E-02)
COAST1000	7.71E-02***	8.61E-02***
	(1.11E-02)	(1.09E-02)
COAST2000	7.76E-02***	7.76E-02***
	(9.74E-03)	(9.54E-03)
COAST3000	1.31E-01***	1.26E-01***
	(1.04E-02)	(1.02E-02)
COAST4000	5.65E-02***	5.74E-02***
	(1.06E-02)	(1.04E-02)
COAST5000	3.67E-03	7.66E-03
	(1.17E-02)	(1.15E-02)
OWNEROCCUPIED*FLDZONVVE		3.20E-01**
		(1.25E-01)
OWNEROCCUPIED*FLDZONAAE		2.22E-01***
		(1.72E-02)
OWNEROCCUPIED*FP500		-7.94E-02**
		(3.34E-02)

R-squared	0.6278	0.6436
Num. of Obs.	33,984	33,984

Significant Codes: *** p<0.01, ** <p<0.05, * p<0.1

Table 3.3 shows the results from the DD model (Model 3) using housing tenureship (OWNEROCCUPIED) and aggregate floodplain variables where both models give the results as in equation (3). Model 4 uses only the data for sales recorded prior Hurricane Sandy (from Jan-2010 to Oct-2012). The total number of sales for Model 3 and Model 4 are 33,930 and 13,064, respectively. In both models, aggregate floodplain variable (FLDZONAAE) and housing tenureship variable (OWNERSHIP) show 1% significant level with a negative sign and a positive sign, respectively, on their coefficient values. The aggregate floodplain and housing tenureship (OWNEROCCUPIED*FLDZONAAE) interaction term, hence, shows 1% statistical significance and a positive sign on its coefficient value. Further from Table 3.3, significant and negative signs on the coefficient values in the (FLDZONVVE*ASANDY), (FLDZONAAE*ASANDY) and (FP500*ASANDY) interaction terms suggest that there were significant impacts on the real property prices in the A/AE, V/VE, and X/X500 flood zones because of the occurrence of Hurricane Sandy. However, property prices for owner-occupied real properties increased after Hurricane Sandy hit the area as suggested by a significant coefficient in the (OWNEROCCUPIED*ASANDY) interaction term. Overall, the R-squared values of 0.64 for both models indicate that the regression line approximates the real observations.

Table 3.3: Regression results from difference-in-differences (DD) model using FEMA flood hazard zones and excluding sales occurred after Hurricane Sandy. Dependent variable is a log-transformed variable of sale price

	Model (3)	**Model (4)**
(Intercept)	1.158e+01***	1.14E+01***
	(8.415e-02)	(1.34E-01)
acs_pctcoll	7.904e-03***	8.64E-03***
	(2.477e-04)	(3.70E-04)
acs_renttotal	8.718e-05***	1.72E-04***
	(2.381e-05)	(4.02E-05)
acs_medincome	1.563e-06***	1.22E-06***
	(1.192e-07)	(1.84E-07)
acs_hhsizetotal	-2.786e-02***	-3.73E-03
	(6.320e-03)	(9.67E-03)
acs_pctvacant	9.591e-03***	9.22E-03***
	(2.716e-04)	(4.73E-04)
acs_pctblack	-6.787e-03***	-7.93E-03***
	(3.698e-04)	(5.83E-04)
OWNEROCCUPIED	1.777e-01***	1.86E-01***
	(1.035e-02)	(1.13E-02)
SEWER	-1.007e-01***	-1.43E-01***
	(1.260e-02)	(2.06E-02)
WATER	-2.524e-02**	-3.45E-04
	(1.139e-02)	(1.86E-02)
GAS	9.682e-02***	8.00E-02***
	(1.105e-02)	(1.81E-02)
SEPTIC	1.034e-02	-3.61E-03
	(1.307e-02)	(2.14E-02)
BLDGAGE	-1.714e-03***	-1.55E-03***
	(1.649e-04)	(2.67E-04)
SQFT	2.149e-04***	1.97E-04***
	(3.741e-06)	(5.62E-06)
CONDITION	3.780e-01***	2.34E-01**
	(3.680e-02)	(7.14E-02)
ROOMS	7.525e-02***	8.31E-02***
	(2.057e-03)	(3.21E-03)
HEIGHT	5.452e-02***	5.52E-02***
	(6.065e-03)	(9.90E-03)

FCONCBLK	6.679e-02 (5.398e-02)	9.04E-02 (8.40E-02)
FCONCSLB	-9.833e-03 (5.430e-02)	1.62E-02 (8.46E-02)
FCONCPOUR	1.418e-01*** (5.478e-02)	1.86E-01** (8.54E-02)
FPIERPIL	1.975e-01** (8.736e-02)	2.27E-01* (1.28E-01)
FSTNBRK	1.306e-01** (5.549e-02)	1.48E-01* (8.65E-02)
hasAC	1.826e-01*** (7.045e-03)	1.55E-01*** (1.16E-02)
hasFIREPLACE	6.037e-02*** (7.724e-03)	6.86E-02*** (1.25E-02)
hasDORMER	-3.903e-02*** (7.656e-03)	-3.07E-02** (1.24E-02)
hasDECK	3.855e-02*** (4.969e-03)	4.41E-02*** (8.08E-03)
hasDOCK	4.111e-01*** (3.318e-02)	4.33E-01*** (5.26E-02)
hasPOOL	9.290e-02*** (1.512e-02)	1.26E-01*** (2.34E-02)
hasSHED1STY	8.817e-03 (5.664e-03)	3.06E-02*** (9.19E-03)
hasBRICK	1.520e-02*** (5.886e-03)	2.62E-02** (9.65E-03)
POSTFIRM	-4.620e-02*** (8.260e-03)	-1.92E-02 (1.35E-02)
LDSTREAM	-7.992e-04 (2.866e-03)	2.56E-03 (4.61E-03)
LDBUSSTO	8.041e-03*** (2.748e-03)	8.75E-03* (4.51E-03)
LDRAILST	-6.196e-02*** (2.892e-03)	-5.58E-02*** (4.71E-03)
LDPOLICE	-3.359e-02*** (4.017e-03)	-4.92E-02*** (6.43E-03)
LDPOLLUT	5.493e-02*** (4.100e-03)	6.87E-02*** (6.70E-03)
LDSCHOOL	-2.424e-02*** (4.100e-03)	-2.63E-02*** (6.71E-03)

FLDZONVVE	7.721e-02	2.71E-03
	(1.216e-01)	(1.55E-01)
FLDZONAAE	-3.087e-01***	-2.70E-01***
	(1.855e-02)	(2.63E-02)
FP500	6.227e-02*	2.46E-02
	(3.484e-02)	(5.11E-02)
COAST500	2.185e-01***	2.55E-01***
	(1.234e-02)	(2.04E-02)
COAST1000	8.300e-02***	9.37E-02***
	(1.087e-02)	(1.75E-02)
COAST2000	7.674e-02***	8.30E-02***
	(9.507e-03)	(1.58E-02)
COAST3000	1.244e-01***	1.18E-01***
	(1.012e-02)	(1.66E-02)
COAST4000	5.704e-02***	5.38E-02***
	(1.032e-02)	(1.69E-02)
COAST5000	6.332e-03	2.51E-03
	(1.145e-02)	(1.86E-02)
OWNEROCCUPIED*FLDZONVVE	3.201e-01**	3.81E-01*
	(1.246e-01)	(1.92E-01)
OWNEROCCUPIED*FLDZONAAE	2.102e-01***	1.41E-01***
	(1.715e-02)	(2.87E-02)
OWNEROCCUPIED*FP500	-8.474e-02**	-4.53E-02
	(3.336e-02)	(5.59E-02)
ASANDY	-6.370e-02***	
	(1.155e-02)	
FLDZONVVE*ASANDY	-2.774e-01**	
	(1.215e-01)	
FLDZONAAE*ASANDY	-1.289e-01***	
	(1.573e-02)	
FP500*ASANDY	-6.063e-02**	
	(2.733e-02)	
OWNEROCCUPIED*ASANDY	3.172e-02**	
	(1.243e-02)	
R-squared	0.6458	0.6411
Num. of Obs.	33930	13064

Significant Codes: *** p<0.01, ** <p<0.05, * p<0.1

Table 3.4 reports the results from the two spatial hedonic property pricing models of owner-occupied and absentee-owner properties that were sold after Hurricane Sandy made a landfall, accounting for spatial dependence in the dependent variable (LSALEPRICE) and the error term (**e**). The expected values of Moran's I for spatial datasets reasoned to construct both models present very low negative values (-0.0000604 for Model 5 and -0.00024 for Model 6), suggesting, however, there is almost no evidence of negative auto-correlation here. While Model 5 has a sample size of 16,562 sales, Model 6 has a sample size of 4,043 sales. Both models use aggregate floodplain variables (FLDZONVVE, FLDZONAAE, FP500), aggregate distance to nearest coastline variables (COAST500 and in the 1000 foot increments), aggregate month of sale (ASANDY1M and in the 1-month increment), and inundation (INUNDATED). Consistent with the regression results in Table 3.3, Table 3.4 also shows discounts for real properties on floodzone A/AE when also controlling for the spatial dependence. There is a significant impact on the property prices for owner-occupied real properties located in various proximity to nearest coastline as suggested by positive and significant coefficients for aggregate distance to nearest coastline variables. Negative sign and significant coefficients for owner-occupied properties sold 4 months and 5 months after Hurricane Sandy (ASANDY4M and ASANDY5M) suggest low sales prices for these properties. Owner-occupied properties that were flooded because of Sandy decreased in prices as suggested by negative and significant coefficients on INUNDATED.

The overall interpretation of the two models show that Rho and Lambda are positive and significant as indicated by Wald test on the explanatory variables. The Likelihood Ratio test of spatial lag and spatial error dependence are also significant. The values of Akaike Info Citerion (AIC) also show that both spatial lag and spatial error of both models fit to the real data points on sales.

Table 3.4: Regression results from the spatial hedonic property pricing model. Dependent variable is a log-transformed variable of sale price

	Model (5)		**Model (6)**	
	Spatial Lag	**Spatial Error**	**Spatial Lag**	**Spatial Error**
(Intercept)	7.0206e+00*** (7.3166e-02)	1.2041e+01*** (1.2365e-01)	7.2107e+00*** (2.4128e-01)	1.2076e+01*** (3.5291e-01)
acs_pctcoll	3.0579e-03*** (2.9544e-04)	6.0619e-03*** (5.3048e-04)	4.8720e-03*** (9.2216e-04)	7.7372e-03*** (1.3683e-03)
acs_renttotal	-1.5097e-05 (NA)	1.0644e-04** (4.6155e-05)	1.0282e-04 (9.0598e-05)	1.8587e-04 (1.1925e-04)
acs_medincome	8.5594e-07*** (1.3828e-07)	2.5344e-06*** (2.4568e-07)	6.5117e-07 (4.6900e-07)	2.2758e-06*** (6.7531e-07)
acs_hhsizetotal	-4.4818e-02*** (7.4208e-03)	-2.9243e-02** (1.3397e-02)	-2.3047e-02 (2.0253e-02)	-1.8018e-02 (3.3377e-02)
acs_pctvacant	4.8343e-03*** (3.1169e-04)	7.6117e-03*** (5.7941e-04)	6.7320e-03*** (7.6617e-04)	1.2278e-02*** (1.2106e-03)
acs_pctblack	-2.7107e-03*** (3.7930e-04)	-4.2259e-03*** (8.2646e-04)	-5.0881e-03*** (1.1494e-03)	-8.2764e-03*** (1.7569e-03)
SEWER	4.4933e-03 (NA)	1.4102e-02 (1.8972e-02)	-1.1355e-02 (NA)	3.4511e-02 (6.7223e-02)
WATER	-3.5751e-02*** (8.8075e-03)	-3.7602e-02** (1.6899e-02)	-2.7939e-02 (3.3842e-02)	-6.1729e-02 (6.3229e-02)
GAS	1.5997e-02 (1.1503e-02)	6.1427e-02*** (2.1988e-02)	1.5216e-01*** (3.6323e-02)	2.5261e-01*** (5.8070e-02)
SEPTIC	-2.2183e-02* (1.1830e-02)	1.8806e-02(2.0310e-02)	-2.9601e-02(4.5432e-02)	-1.8340e-03(6.4071e-02)
BLDGAGE	-1.9088e-03*** (1.5231e-04)	-2.4838e-03*** (2.1266e-04)	-1.3850e-03*** (3.6772e-04)	-1.6397e-03*** (5.9279e-04)
SQFT	1.8543e-04*** (4.1767e-06)	2.0372e-04*** (4.4971e-06)	2.3993e-04 (1.2777e-05)	2.4563e-04*** (1.3801e-05)
CONDITION	2.0256e-01*** (4.9309e-02)	1.7063e-01*** (5.0642e-02)	4.4225e-01*** (8.5844e-02)	3.6663e-01*** (1.0469e-01)
ROOMS	3.9249e-02*** (2.2260e-03)	3.9329e-02*** (2.3497e-03)	3.1182e-02*** (6.2958e-03)	3.1945e-02*** (6.4385e-03)
HEIGHT	5.2070e-02*** (6.6712e-03)	7.1303e-02*** (7.5508e-03)	5.1159e-02** (2.0817e-02)	5.6329e-02** (2.3941e-02)
FCONCBLK	-1.7210e-01*** (2.3851e-02)	-2.0246e-01*** (2.6742e-02)	-2.9130e-01*** (4.6057e-02)	-3.1333e-01*** (4.9268e-02)

FCONCSLB	-2.1147e-01*** (2.4783e-02)	-2.5370e-01*** (2.7822e-02)	-3.3049e-01*** (5.0754e-02)	-3.5574e-01*** (5.5453e-02)
FCONCPOUR	-1.4307e-01*** (2.5944e-02)	-1.6521e-01*** (2.9280e-02)	-2.4968e-01*** (5.9263e-02)	-2.4200e-01*** (6.4576e-02)
FPIERPIL	5.2748e-02 (8.8138e-02)	1.2268e-04 (9.8474e-02)	-2.8783e-01 (2.2169e-01)	-2.0030e-01 (2.2659e-01)
FSTNBRK	-1.0410e-01*** (2.9570e-02)	-1.4027e-01*** (3.2115e-02)	-2.6746e-01*** (6.4869e-02)	-2.8199e-01*** (6.8454e-02)
hasAC	1.5102e-01*** (8.1531e-03)	1.4621e-01*** (8.6103e-03)	1.3981e-01*** (2.2531e-02)	1.2247e-01*** (2.3636e-02)
hasFIREPLACE	2.7406e-02*** (7.5507e-03)	3.4399e-02*** (8.5108e-03)	-6.2624e-03 (NA)	-2.2037e-03 (3.5497e-02)
hasDORMER	-3.8828e-02*** (8.1621e-03)	-3.0058e-02*** (8.7328e-03)	-5.5831e-02** (2.8286e-02)	-4.1227e-02 (2.8745e-02)
hasDECK	2.5133e-02*** (5.3325e-03)	2.3904e-02*** (5.6217e-03)	3.1646e-02* (1.8997e-02)	4.3661e-02** (1.9882e-02)
hasDOCK	2.4562e-01*** (3.6228e-02)	2.3567e-01*** (3.9537e-02)	4.9591e-01*** (1.1024e-01)	4.9513e-01*** (1.1121e-01)
hasPOOL	5.4788e-02*** (1.6007e-02)	7.2160e-02*** (1.6667e-02)	1.9723e-02 (4.4198e-02)	4.1007e-02 (7.6798e-02)
hasSHED1STY	4.9471e-03 (NA)	7.9253e-03 (6.4190e-03)	-4.9174e-02** (2.3035e-02)	-4.3729e-02* (2.3447e-02)
hasBRICK	-1.2257e-02*** (3.8253e-03)	3.0013e-03 (7.0180e-03)	2.4617e-03 (NA)	3.2103e-02 (2.8197e-02)
POSTFIRM	-4.1100e-02*** (8.8357e-03)	-4.1123e-02*** (1.1642e-02)	2.9733e-03 (NA)	2.1121e-02 (3.7107e-02)
LDSTREAM	3.8179e-03 (NA)	6.3051e-03 (4.8278e-03)	-1.0991e-03 (1.1356e-03)	-8.9980e-03 (1.4825e-02)
LDBUSSTO	-4.4915e-03*** (1.1016e-03)	1.2518e-02** (5.8985e-03)	-3.1800e-03 (NA)	2.0335e-02 (1.5766e-02)
LDRAILST	-3.5516e-02*** (3.2464e-03)	-6.8641e-02*** (6.4519e-03)	-5.2573e-02*** (1.0676e-02)	-1.3269e-01*** (1.7882e-02)
LDPOLICE	-1.1895e-02*** (3.1743e-03)	-3.4123e-02*** (9.0110e-03)	-1.1755e-02 (1.2057e-02)	-2.6109e-02 (2.3324e-02)
LDPOLLUT	1.3714e-02*** (4.2801e-03)	5.9735e-02*** (8.2901e-03)	4.5189e-02*** (1.3847e-02)	9.0642e-02*** (2.0992e-02)
LDSCHOOL	-1.4411e-02*** (4.5782e-03)	-8.9424e-03 (8.4344e-03)	-1.9597e-02 (1.4067e-02)	-4.4270e-03(2.2993e-02)
FLDZONVVE	3.8334e-01*** (7.6468e-02)	3.2144e-01*** (7.7834e-02)	1.1885e-01 (1.6088e-01)	5.9017e-02(2.0079e-01)
FLDZONAAE	-9.8214e-02*** (1.1133e-02)	-8.5838e-02*** (1.4738e-02)	-2.8290e-01*** (3.0945e-02)	-3.3340e-01*** (3.9952e-02)
FP500	-4.0251e-02*** (1.4224e-02)	-2.2433e-02 (1.8964e-02)	3.3473e-02 (4.2787e-02)	-3.9504e-04 (5.2938e-02)

COAST500	1.2972e-01*** (1.3879e-02)	1.8831e-01*** (2.2735e-02)	2.0309e-01*** (3.6797e-02)	1.5829e-01*** (5.7941e-02)
COAST1000	6.2391e-02*** (1.2325e-02)	7.2084e-02*** (2.0208e-02)	2.7501e-02 (3.1693e-02)	-5.0777e-02 (5.4887e-02)
COAST2000	5.9357e-02*** (9.8959e-03)	6.8438e-02*** (1.8522e-02)	2.3681e-02 (2.5557e-02)	-3.9143e-02 (5.2462e-02)
COAST3000	9.0937e-02*** (1.0273e-02)	9.4892e-02*** (1.9161e-02)	1.1056e-01*** (3.5588e-02)	8.6587e-02 (5.7170e-02)
COAST4000	5.2399e-02*** (1.0312e-02)	6.7157e-02*** (1.9459e-02)	3.6020e-02 (3.9281e-02)	4.0083e-03 (5.9375e-02)
COAST5000	2.8178e-02*** (1.0419e-02)	3.7578e-02* (2.0216e-02)	-3.9534e-02 (4.6978e-02)	-7.2300e-02 (6.0727e-02)
ASANDY1M	-2.2141e-0 2(1.6256e-02)	-1.4417e-02 (1.7810e-02)	5.8928e-02 (5.5396e-02)	2.7704e-02 (6.0439e-02)
ASANDY2M	3.1747e-03 (NA)	2.1480e-03 (1.8392e-02)	-1.1605e-01* (6.3837e-02)	-1.2030e-01* (6.2308e-02)
ASANDY3M	7.5533e-03 (6.8345e-03)	-1.7446e-03 (1.8983e-02)	2.7331e-02 (6.2023e-02)	2.3013e-04 (6.8894e-02)
ASANDY4M	-6.2750e-02*** (1.7150e-02)	-5.0609e-02*** (1.6700e-02)	-4.6902e-02 (5.4613e-02)	-5.2565e-02 (5.9077e-02)
ASANDY5M	-8.2867e-02*** (2.2659e-02)	-8.8155e-02*** (2.2502e-02)	-2.3733e-02 (5.9669e-02)	-2.1937e-02 (7.6875e-02)
INUNDATED	-3.6258e-02** (1.6334e-02)	6.2951e-04(1.9912e-02)	-3.7550e-02 (3.6345e-02)	-3.9034e-02 (4.2743e-02)
Rho	0.43319		0.40039	
Lambda		0.5164		0.4372
num-obs	16562	16562	4043	4043
LR-test (p-val)	3727.9 (<0.000)	2993 (<0.000)	619.04 (<0.000)	485.49 (<0.000)
num-Hessian std. err.	0.0063987	0.0079789	0.014684	0.018303
z-val (p-val)	67.7 (<0.000)	64.721 (<0.000)	27.268 (<0.000)	23.888 (<0.000)
Wald-stat (p-val)	4583.2 (<0.000)	4188.8 (<0.000)	743.55 (<0.000)	570.62 (<0.000)
Log-likelihood	-5419.979	-5787.429	-3359.801	-3426.577
sigma-squared (sigma)	0.1079 (0.32848)	0.11035 (0.3322)	0.29784 (0.54575)	0.30546 (0.55268)
num-par	53	53	53	53
AIC (AIC for lm)	10946 (14672)	11681 (14672)	6825.6 (7442.6)	6959.2 (7442.6)

Significant Codes: *** p<0.01, ** <p<0.05, * p<0.1

3.5. Conclusions

This chapter provides analyses on the flood risk measures by using floodplain maps and a flood inundation map, and housing tenureship pattern. These measures determine the impact of the storm surge related flooding caused by Hurricane Sandy on the real property markets in Monmouth County, New Jersey.

The findings from the analyses suggest an increasing discount for real properties located in the floodplain, particularly in the areas with high-flood risk (A zone and AE zone). In other words, FEMA floodplain maps apparently inform the decisions of purchasing real properties, which accord with the literature (Atreya 2013; Tversky and Kahneman 1973). Waterfront properties are valued more than bay properties despite the locations are highly vulnerable to flood risk. Prices of owner-occupied properties are higher than the prices of absentee-owner properties. On the impacts of Sandy, property sales are higher before flooding than in the aftermath, suggesting that flood risk is capitalized in the price at the time of sale. The drops in house prices are widespread and affect a larger part of the community. This indicates the decline in urban investment. Chapter 5 of this dissertation explores more how the decline is reflected in the changes in population and household income. There is no significant discount on sales within the floodplain properties after Sandy. Price discount is especially noticed on the sales of Pre-FIRM properties after Sandy. Sandy also discounted sales for owner-occupied properties much less than absentee-owners'.

Findings from the spatial hedonic analyses indicate discounts for real properties that were flooded from Sandy, particularly for the sales that were made within 4 to 5 months after Sandy hit the area. Price discounts are also found among the owneroccupied properties that were sold after Sandy. Absentee-owner properties were sold at lower prices on the 2nd month after sandy.

Chapter 4

Flood Insurance in Monmouth County, NJ

Abstract

This chapter seeks to test the fourth hypothesis, the "National Flood Insurance Program (NFIP) has the unanticipated consequence of moral hazard to encourage development in flood risk areas". In order to test the hypothesis, the analysis is divided into two parts. At the municipality level, the analysis uses OLS regression as well as fixed effects and random effects. The second is an analysis at the property level, which employs a generalized spatial two stage least squares (GS2SLS) estimation. The analysis includes estimators, such as structural characteristics and neighborhood characteristics of real properties. Also, the analysis focuses on the effects of flood risk indicators such as FEMA floodplain maps and distance to the nearest coastline as well as housing tenureship on the total amount of claims).

4.1. Introduction

The U.S. Congress established the National Flood Insurance Program (NFIP) through the National Flood Insurance Act of 1968. The NFIP was created because of two reasons: private insurance market does not provide adequate flood insurance and the government has been financially burdened for flood recovery relief. The program is managed by the Federal Emergency Management Agency (FEMA) with three goals, which are as follows: to protect homeowners from losses through flood insurance; to mitigate flood damages through management and regulation; and to minimize federal expenditures for disaster relief and flood control (FEMA, 2002). The NFIP provides flood insurance coverage to communities that choose to adopt minimum requirements of floodplain management policies. FEMA identifies floodplain areas (or the Special Flood Hazard Area, SFHA[7]), assesses flood risk, and determines premiums for the NFIP through the Flood Insurance Rate Maps (FIRMs). The risk assessment uses aggregate historical flood records and a technique that is similarly used by the private insurance market. In 1973, Congress required all homeowners, whose properties are located in 100-year floodplain, to purchase flood insurance with a mortgage from federally backed or regulated banks. The 100-year flood is a flood event having 1% or greater probability of flooding in any year (U.S. Geological Survey, 2010). The inundated area as a result of a 100-year flood is called 100-year floodplain.

In the implementation, the NFIP has been the subject of debates for reform, mainly for financial reasons. In 2005, Hurricanes Katrina and Rita have left the NFIP with $17 billion of debt and had to borrow from the treasury (Cooper & Block, 2006). The amount of payouts from the 2012 Hurricane Sandy have increased the debt of NFIP by $2.95 billion. In the aftermath of Hurricane Sandy in 2012, the Biggert-Waters Flood Insurance Reform Act of 2012 (Biggert-Waters Act) was enacted to strengthen financial soundness of the program by including premiums in mortgage escrow accounts, thus, allowing mortgage lenders to maintain coverage (Orie, 2013). The implementation, however, remained unclear, resulting in the Homeowner Flood Insurance Affordability Act of 2014 (HFIAA) to reinstate premium rates prior to those that had been included in

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[7] Special Flood Hazard Area (SFHA) is the area where the National Flood Insurance Program's (NFIP) floodplain management regulations must be enforced and the area where the mandatory purchase of flood insurance applies. The SFHA includes Zones A, AE, V, and VE. (FEMA)

the Biggert-Waters Act. Similar to the earlier initiatives, HFIAA was intended to encourage flood insurance purchase by increasing affordability; however, the financial burden on taxpayers may as well increase. This chapter seeks to understand the financial problem within the NFIP by looking at the drivers of flood insurance purchase at municipality level as well as the factors explaining the increase of flood insurance claims at property level.

Nationally, the number of flood insurance policyholders is highly concentrated in five states: Florida, Texas, Louisiana, California, and New Jersey; which make up to 70% of all policies in force (Michel-Kerjan and Kousky, 2010). As of August 31st 2016, there were 232,347 policies-in-force, the total premium collected was $229,146,660 and the total coverage was $5,895,290,693.17 in New Jersey (FEMA, 2016). The 2012 Hurricane Sandy and Hurricane Irene that hit New Jersey have caused the flood insurance claims to exceed the premium collected. This suggests that communities in New Jersey, like those in other U.S. states, were not ready to pay the costs before a flood event. This has attracted criticism that the evaluation of NFIP performance has been done only after a flood event.

The NFIP considers the eligibility of participating communities to purchase flood insurance by requiring homeowners to adopt FEMA recommended building and land use codes as part of the flood risk reduction measures (Burby, 2001; Burby & French, 1981). FEMA also uses the Community Rating System (CRS) to assess communities (FEMA, 2015). CRS is an incentive program to encourage communities to exceed the minimum NFIP requirements. Through voluntary participation, communities receive points that will discount their insurance premium rate up to 45%. In Monmouth County only 13 municipalities of 53 municipalities participate in the CRS. Homeowners whose properties fail to meet building codes and zoning regulations often contribute the largest proportion of the total amount of flood insurance claims. The benefits of participating communities in the NFIP, however, may reflect the behavior of property owners differently. Earlier studies have shown the relationship between NFIP's price and payouts and the household's income. Homeowners with higher incomes purchase a greater amount of flood insurance than homeowners in the lower income bracket (Brown & Hoyt, 2000; Kriesel and Landry, 2004; Landry and Jahan-Parvar, 2008).

Perception of flood risk also influences homeowners' decision to purchase flood insurance. A study by Kousky (2008) shows that flood protection structures such as a levee and seawall lower homeowners' willingness to purchase flood insurance, despite records of failures of the levees (e.g. The Midwest Floods in 1993 and Hurricane Katrina in 2005). While the flood protection measures are commonly found in both coastal flood risk and riverine flood risk areas, flood insurance purchase is more prevalent among residents in riverine areas (Kriesel and Landry, 2004). Moreover, homeowners perceive the outcomes of prior flood events tend to be better than to other disaster events such as fire. Therefore, a perception that the loss from flood damages tends to be less than those made by fire, negatively affect flood insurance purchase among homeowners. A survey conducted to the NFIP policyholders in Nevada puts the mortgage requirement and flood risk awareness among the top reasons for homeowners to purchase flood insurance (Yildirim, 1997). Homeowners also purchase flood insurance after the experience of flooding. According to Moore & Cantrell (1976), recent flood events increase the awareness on flood risk. However, an impression that flood risk has a short-term impact also results in early termination of insurance policies (Michel-Kerjan et al., 2012).

Co-existing federal policies correlate either positively or negatively with purchasing flood insurance through the NFIP. Since the enactment of the Disaster Relief Act of 1974 (DRA), the program has discouraged NFIP participating homeowners to use relief aid under the DRA without any proof of mitigation measures. In contrast, the FEMA-sponsored Community Rating System program (CRS) has encouraged homeowners to purchase NFIP insurance through the premium discounts they receive.

A review from the literature also suggests that purchasing flood insurance can lead to moral hazard. Zahran et al. (2008) defines moral hazard as changes in peoples' behavior to be taking riskier decisions because of more reliance on protection offered by policy or programs. A study conducted in the state of Florida, showed that the NFIP incentivizes people to move their homes to floodplain areas through underwriting and underpriced insurance (Boulware, 2009). This scenario suggests that the risk takers among the NFIP policyholders probably contribute a large amount of flood insurance payouts.

Failing to meet zoning regulations and building codes expose real properties to flood risk. The scenario, hence, contributes significantly to the amount of flood insurance claims. Homeowners, whose properties are subject to storm surge and located in 100-year floodplain, file 35% more claims than those are outside the 100-year or 500-year floodplain (Kousky and Michel-Kerjan, 2015). Homeowners, who protect their properties with certain flood control measures (i.e. elevating homes), have lower payouts by 16-18 percent than those, who do not install any flood defense measures. Other physical characteristics such as having more than one floor or a basement also lower the payouts.

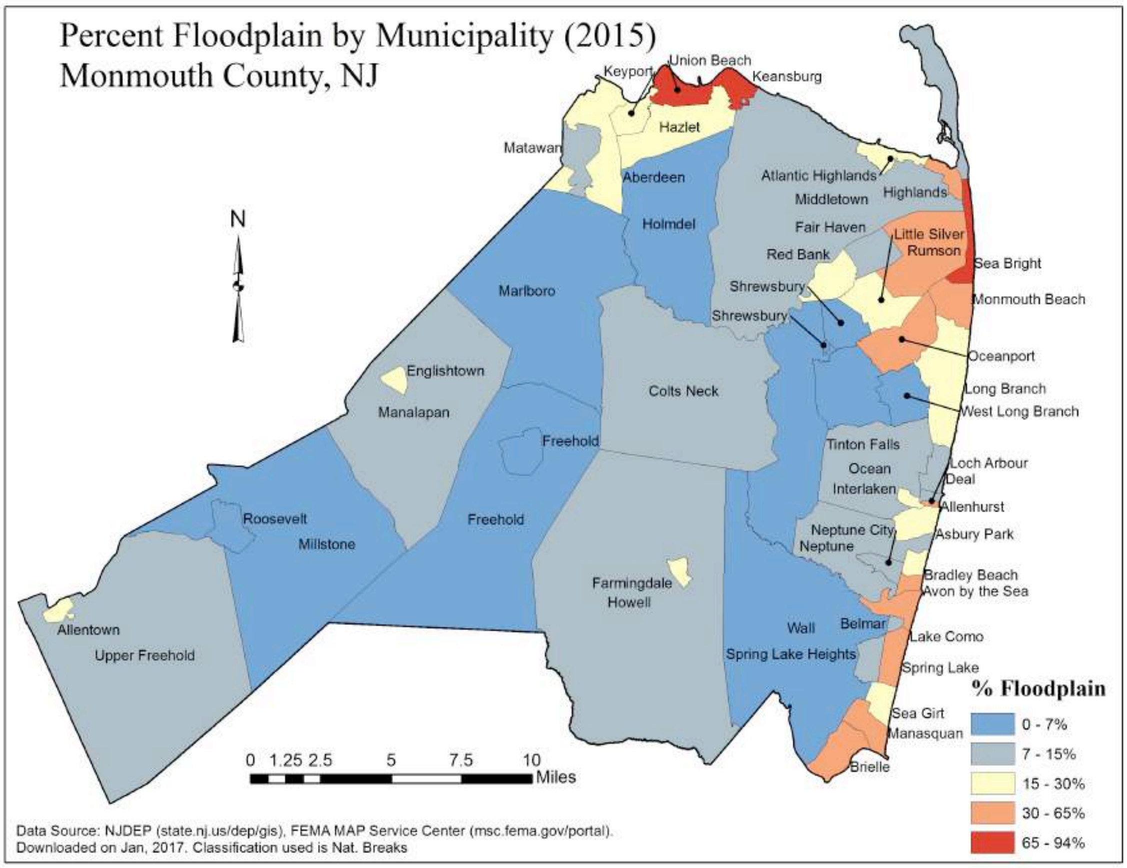
In general, there are two categories of real properties that burden the NFIP financially. The first is floodplain properties that were built prior to the FEMA floodplain maps in 1974, also called as "pre-FIRM" properties. Pre-FIRM properties have 42-45 percent higher claims than other properties. Real properties in the second category (i.e. "repetitive loss" properties) have claims higher than others, by 5-20 percent. Homeowners of these properties experience two or more losses of at least $1,000 within 10-year period. Findings from Kousky and Michel-Kerjan (2015) also suggest lower flood insurance payouts among communities that engage in the flood mitigation efforts than those, who do not.

Another category of real properties worth analyzing is housing tenureship. Real properties in Monmouth County, New Jersey are varied in terms of tenureship. Absentee-owner properties (renter-occupied homes and seasonal homes) are commonly found close to the coastline. The proportion of these absentee-owner properties can be as high as 19 percent. Many of these properties are located within the FEMA floodplain maps. Therefore, this study also aims to investigate the flood insurance market patterns based on housing tenureship.

4.2. Flood Insurance Market in Monmouth County, NJ

This study looks at the flood insurance market in Monmouth County, New Jersey. Properties in Monmouth County are among those coastal counties that were hit the hardest by the 2012 Hurricane Sandy. FEMA reported that Monmouth County had $172 million of flood damage from Sandy with major destruction in Asbury Park, Belmar, Sea Bright, Union Beach, Sayreville, and Highlands. Out of $5.3 billion of total Federal Assistance, the total NFIP payments made on claims were $3.5 billion, or about 66 percent[8].

These communities are vulnerable to flood because many are located in flood prone areas. Figure 4.1 illustrates the percentage of floodplain areas by municipality in Monmouth County, NJ, in the year of 2015. Most of floodplain properties are located in coastal towns. Sea Bright has the highest proportion of floodplain with 93.18 percent, followed by Union Beach (87%) and Manasquan (87%).



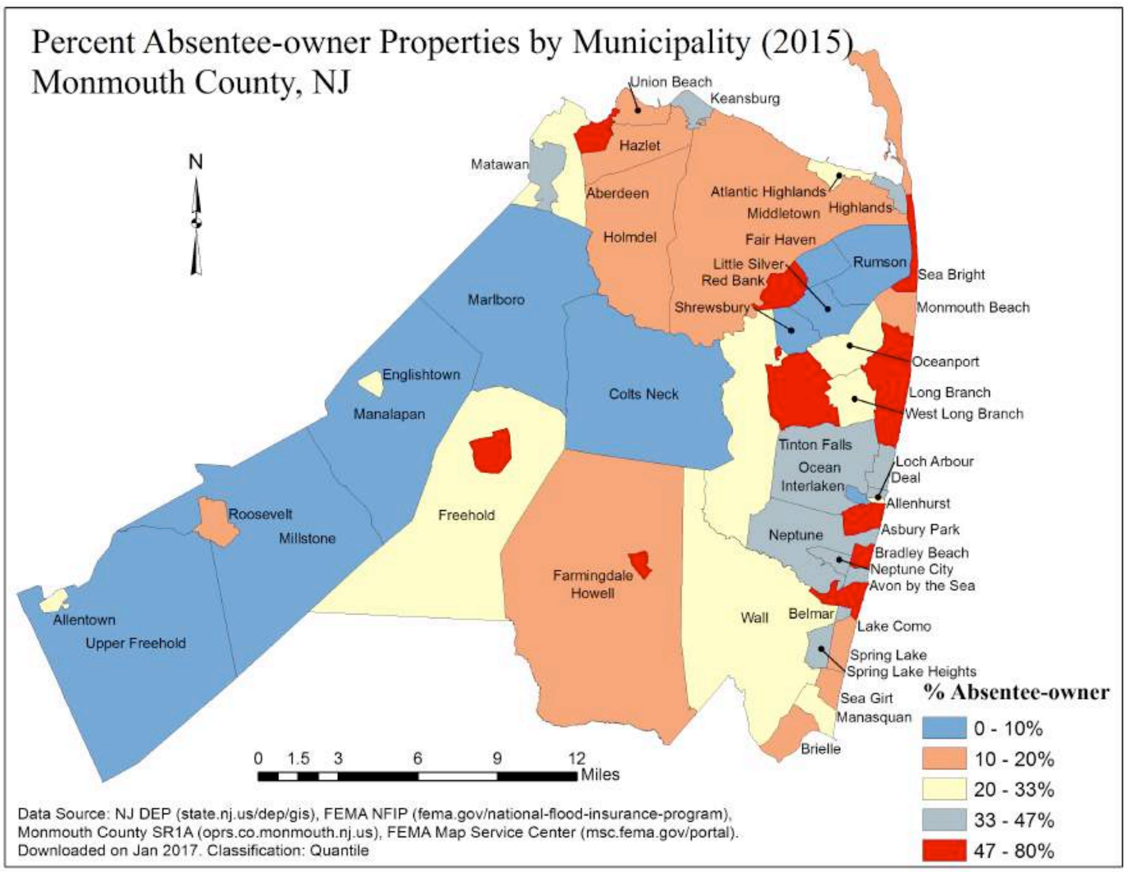
Data source: FEMA floodplain maps, NJ DEP

Figure 4.1: Percentage of floodplain by municipality in Monmouth County, NJ, in 2015

There is an obvious relation between the proportion of floodplain areas and

[8] FEMA press release. "New Jersey Recovery from Super Storm Sandy: By the Numbers," July 15, 2013. https://www.fema.gov/news-release/2013/07/15/new-jersey-recovery-superstorm-sandy-numbers.

housing tenureship within a municipality. Real properties that are renter-occupied or seasonal type or other types of absentee occupancy are mainly located near the coastline. These properties are vulnerable to surge damages during large storm events. As illustrated in Figure 4.2, there are six municipalities with 50 percent or more of absentee-owner properties. They are Asbury Park (79.8%), Long Branch (58%), Bradley Beach (56.8), Red Bank (53), Belmar (50.9), Shrewsbury Township (50.9%). Properties in these coastal towns were badly damaged by Hurricane Sandy in 2012 and caused billions of dollars in the flood insurance payouts.



Data source: NJ DEP, U. S. Census American Community Survey, FEMA floodplain map, FEMA National Flood Insurance Program (NFIP)

Figure 4.2: Housing tenureship by municipality in Monmouth County, NJ, in 2015

4.3. Data

For the analyses, the municipalities' characteristics are collected from the U.S. Census Decennial 2010 and American Community Survey (ACS) 2010 – 3-year data. The number of building permits for each municipality is based on the data provided by the State of New Jersey Department of Community Affairs. The data on NFIP's policies in force (PIF) as well as the number of claims are provided by FEMA for the period 2000-2014. The floodplain maps for Monmouth County are also provided by FEMA.

Table 4.1 illustrates the total policies-in-force in Monmouth County, NJ, over the period 2000-2014. The number of NFIP policies has increased by almost 64 percent, which is reflected in the increase in the amount of premiums by 189 percent during the period. The increase was, however, overpowered by the increase in the amount of claims paid to the homeowners by 382 percent during the same period. It is also noticeable that when Hurricane Irene and Hurricane Sandy made landfalls in 2011 and 2012, the total payout exceeded the expected payout calculated from the premiums accumulated over several years. The amount of premiums rebounded and increased for 12 percent in the following year. The impact of Sandy affected various insurance categories, namely: property, business, civil authority, ingress, and egress, event cancellation, general liability, and other expenses. Because of this, the program was burdened with an additional $7 billion in debt. The premium rates that were previously capped at 10% in the increase, have jumped 20-25% and will continually increase. Afterwards, Congress also mandated homeowners living in areas with high flood risk to have flood insurance. FEMA has updated the floodplain maps to consider a greater areas of high flood risk.

Table 4.1: Policies-in-force, average premium and average payout in Monmouth County, NJ for the period 2000-2014

Year	Total Policies-In-Force (PIF)	Total Claims	Average claims by municipality ($)	Total Premium Collected ($)	Average premium collected by municipality ($)	% Increase in the collected premiums
2000	14,485	$179,563	$3,388	$7,477,317	$141,081	
2001	14,452	$164,258	$3,099	$7,551,441	$142,480	0.99%
2002	14,734	$262,176	$4,947	$8,103,622	$152,899	7.31%
2003	15,200	$97,052	$1,831	$8,882,209	$167,589	9.61%
2004	15,321	$135,422	$2,555	$9,745,564	$183,879	9.72%
2005	16,260	$7,606,649	$143,522	$10,755,816	$202,940	10.37%
2006	17,443	$169,310	$3,195	$12,225,313	$230,666	13.66%
2007	18,237	$569,175	$10,739	$13,624,374	$257,064	11.44%
2008	18,849	$86,457	$1,631	$15,218,080	$287,134	11.70%
2009	19,815	$120,062	$2,265	$16,057,751	$302,976	5.52%
2010	20,600	$4,140,673	$78,126	$18,021,720	$340,032	12.23%
2011	21,216	$28,454,271	$536,873	$18,223,079	$343,832	1.12%
2012	21,884	$755,346,498	$14,251,821	$19,475,792	$367,468	6.87%
2013	24,049	$161,865	$3,054	$21,810,365	$411,516	11.99%
2014	23,704	$878,326	$16,572	$22,033,370	$415,724	1.02%

Data source: FEMA NFIP

Flood insurance purchase is consistently driven by two categories of attributes, such as neighborhood attributes and location attributes. The neighborhood attributes included in the study are median household income, percent college graduates, percent of age group 25 and above, percent of non-white population, percent of owner-occupied properties, participation in the NFIP = 1 and 0 = otherwise, and participation in the CRS = 1 and 0 = otherwise. The only location attribute is the distance to the nearest coastline. Other relevant attributes of interest are percent flood zones areas (i.e. V/VE, A/AE, X500, and X), coastal towns = 1 and 0 = otherwise.

Table 4.2 shows the summary statistics of all variables considered in the model.

The average policies-in-force (PIF) per- total housing units, which is the dependent variable, is 70.589. The model measures the cost per thousand dollars of flood insurance coverage (NFIPPRICE) by dividing the amount of premiums paid for flood insurance by the amount of insurance coverage (in thousands) in the municipality during the year, which is $159,723 on average. The average percentage of floodplain areas is 24% across all municipalities in Monmouth County as indicated by a variable SFHAPCT. The other variable, BLDGPERMIT, shows that an average number of permits is 35.4.

Table 4.2: Description and the summary statistics of the variables at the municipality level for the period 2000-2014

	Min	**Max**	**Median**	**Mean**	**Std. dev.**
PIF_HOUSING	0	100.58	3.81	12.26	20.16
NFIPPRICE (usd)	0.013	2,340,564	22,285	159,723.3	382,734.8
INCOME (usd)	160	162,909.2	39,809.28	45,276.06	29,730.88
OWNERPCT (%)	19.5	96.64	77.96	73.52	17.83
AGE25PCT (%)	0	97.6	0	23.6	33.6
BLACKPCT (%)	0	62.11	2.21	5.54	9.86
COLLEGEPCT (%)	11.3	73.01	43.65	44.21	14.65
OCCUPIEDPCT (%)	35.96	98.69	94.56	88.55	11.99
PROPVALUECAPITA (usd)	0	3,885,898	166,889	271,027.1	400,080.6
SFHAPCT (%)	0.0058	93.1799	15.4158	23.8398	22.477
COAST (=1)	0	1	1	0.548	0.498
AVGPROPVAL (usd)	151,034	3,191,286	436,821.5	583,996.6	470,029
BLDGPERMIT	0	506	11	35.4	67.2

Data Sources: FEMA NFIP, U.S Census

At the property-level, the structural attributes that may influence the flood insurance premiums and claims include building square footage, number of stories, building age at the time of sales, type of foundation with concrete slab = 1and 0 = otherwise (concrete, concrete block, pier, pipe), exterior wall type with brick = 1 and 0 = otherwise (concrete, metal, wood), a dummy variable for the structure condition with 1 = excellent and 0 = otherwise (poor, average, fair, good, very good), dummy variables for availability of the following features = 1 and 0 = otherwise: attic, basement, air conditioning, forced hot air, Jacuzzi, fireplace, dormer, deck, dock, pool, porch, garage, patio, and first story shed (see table 4.3). Also, the flood risk attributes include flood zones that vary from 100-year floodplain (VE zone, V zone, A zone, and AE zone), 500-year floodplain (X500 zone), and outside 100-year and 500-year floodplains and distance to the nearest coastline. Finally, the housing tenureship attribute captures the different in effects of owner-occupied and absentee-owner properties.

Table 4.3: Description and the summary statistics of the variables at property level

	Min	**Max**	**Median**	**Mean**	**Std. dev**
TOTALPAID (usd)	45.9	1,715,267	35,771.9	58,368.3	78,142.9
OWNEROCCUPIED (=1)	0	1	1	0.7078	0.4548
SEWER (=1)	0	1	1	0.9717	0.1658
WATER (=1)	0	1	1	0.9616	0.1922
GAS (=1)	0	1	0	0.1489	0.356
SEPTIC (=1)	0	1	0	0.00321	0.0566
BLDGAGE (years)	0	157	60	56.74	32.49
ACREAGE (miles)	0	15,590	0.086	7.278	260.292
SQFT (sq.ft.)	0	30,528	1,744	2,047.37	1,545.61
CONDITION (=1)	0	1	0	0.0083	0.0908
ROOMS	0	20	5	5.679	2.095
HEIGHT	1	3	2	1.6768	0.5159
FCONCBLK (=1)	0	1	1	0.8338	0.3723
FCONCSLB (=1)	0	1	0	0.0664	0.249

FCONCPOUR (=1)	0	1	0	0.0499	0.2177
FPIERPIL (=1)	0	1	0	0.0109	0.1038
FSTNBRK (=1)	0	1	0	0.033	0.1787
hasAC (=1)	0	1	1	0.6289	0.4831
hasFIREPLACE (=1)	0	1	0	0.1051	0.3067
hasDORMER (=1)	0	1	1	0.8427	0.3641
hasDECK (=1)	0	1	1	0.605	0.4889
hasDOCK (=1)	0	1	0	0.0439	0.2048
hasSHED1STY (=1)	0	1	0	0.2845	0.4512
hasBRICK (=1)	0	1	0	0.0932	0.2907
hasBASEMENT (=1)	0	1	0	0.0961	0.2947
hasPORCH (=1)	0	1	1	0.6329	0.482
hasPATIO (=1)	0	1	1	0.5425	0.4982
hasATTIC (=1)	0	1	0	0.023	0.1498
POSTFIRM (=1)	0	1	0	0.3563	0.4789
FLDZONAAE (=1)	0	1	1	0.8384	0.3681
FLDZONEVVE (=1)	0	1	0	0.0148	0.1207
FP500 (=1)	0	1	0	0.0684	0.2525
COAST (=1)	0	1	1	0.9354	0.2458
COAST500 (=1)	0	1	0	0.4031	0.4906
COAST1000 (=1)	0	1	0	0.2795	0.4488
COAST2000 (=1)	0	1	0	0.259	0.4381
COAST3000 (=1)	0	1	0	0.027	0.162
COAST4000 (=1)	0	1	0	0.0067	0.0819
COAST5000 (=1)	0	1	0	0.00369	0.06068

Data Sources: FEMA NFIP, NJDEP, Monmouth County MOD IV

4.4. Method

This study examines the demand for flood insurance in Monmouth County, NJ. There are two objectives of this section of the dissertation. The first is to estimate municipality-level flood insurance market penetration rates. The market penetration rate is, basically, the proportion of households in a municipality that have purchased flood insurance. Table 4.4 shows the flood insurance market penetration in 2014 by municipality. The top five municipalities with the highest take up rates for the flood insurance policies in 2014 were Sea Bright (97.7%), Monmouth Beach (93.9%), Union Beach (53.7%), Manasquan (46.1%), and Keansburg (44.7%). Noticed in the table, these municipalities are also among the top municipalities in the proportion of floodplain areas.

Table 4.4: Flood insurance market penetration and proportion of floodplain areas by municipality in 2014

Municipality	PIF/ Housing Units	% Floodplain
Sea Bright	97.7	93.2%
Monmouth Beach	93.9	64.7%
Union Beach	53.7	86.7%
Manasquan	46.1	57.8%
Keansburg	44.7	87.0%
Highlands	37.1	51.3%
Loch Arbour	36.5	63.0%
Spring Lake Boro	35.8	30.2%
Oceanport	31.2	33.9%
Avon-By-The-Sea	31.0	48.0%

Data source: FEMA NFIP

Beyond the demographic characteristics and location attributes, there is also a strong relation between the flood insurance market penetration and the proportion of floodplain within a municipality. In order to examine how these factors impact the flood insurance market penetration rate, a regression model for flood insurance purchase is developed in terms of attributes of the municipality and the county where it resides, Monmouth County, NJ, as illustrated in Equation (1). Also, the cost of insurance coverage, housing tenureship, and building permits are included in the independent variables. The analysis also examines the effect of Hurricane Sandy on the policies take up rates as suggested in the variable Sandy_HHI (Household Hardship Index).

$$\begin{aligned}\ln(\text{PIF/Housing Units}) = {} & \beta_0 + \beta_1\ln(\text{Price}) + \beta_2(\text{Age}) + \beta_3(\text{Race}) + \beta_4(\text{Income}) \\ & + \beta_5(\text{Tenureship}) + \beta_6(\text{Coast}) + \beta_7(\text{Floodplain}) \\ & + \beta_8(\text{Permits}) + \beta_9(\text{Floodplain*Permits}) \\ & + \beta_{10}(\text{Sandy\_HHI}) + \beta_{11}(\text{Sandy\_HHI*Permits}) + e \qquad (1)\end{aligned}$$

At the property level, the analysis looks at the effects of housing tenureship and flood-risks on flood insurance claims as suggested by Equation (2). There are multiple attributes that potentially affect the amount of payouts after a flooding event. Some of the relevant attributes include the property' structural attributes, aggregate distance to coast variables, aggregate floodplain variables, and housing tenureship. The interaction terms of Tenureship*FloodZones and Tenureship*DistanceToCoast are also considered in the model. To take into account spatial autocorrelation, the analysis is divided into three spatial hedonic models that uses specific estimation procedure, namely generalized spatial two stage least square (GS2SLS) estimation. The procedure is used to produce more consistent estimates of a spatially lagged dependent variable and a spatially autocorrelated error term (Kelejian and Purcha 1998; Arraiz et al. 2010).

$$\begin{aligned}\ln(\text{Claims}) = {} & \beta_0 + \beta_1(\text{Structure}) + \beta_2(\text{FloodZones}) + \beta_3(\text{DistanceToCoast}) \\ & + \beta_4(\text{Tenureship}) + \beta_5(\text{Tenureship*FloodZones}) \\ & + \beta_6(\text{Tenureship*DistanceToCoast}) + e \qquad (2)\end{aligned}$$

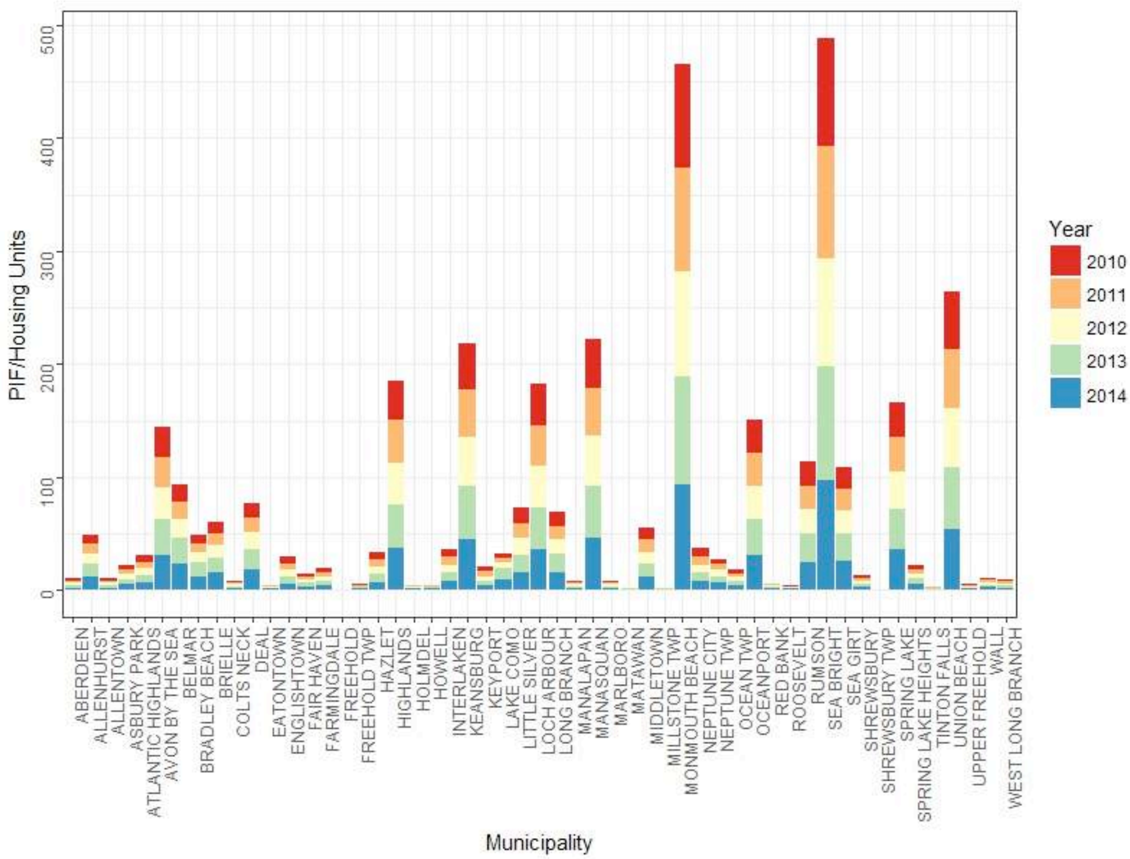
All three models are constructed based on Equation (2). While the baseline model does not include any interaction term, the other two models estimate the effect of housing tenureship under two different flood-risk estimators such as the aggregate floodplain variables and the variables that explain distance to the nearest coastline. All three models are developed based on a total of 6,225 observations.

4.5. Results

This section describes the resulting analyses on the flood insurance market. Seven regression models were developed to test the hypotheses, in which four models were to estimate the flood insurance purchase at the municipality level and three models were to estimate flood insurance claims paid to the policy-holders at the property level. In the next sub-section, a general overview of flood insurance market penetration is discussed by comparing across municipalities and rank them based on important comparable categories such premiums collected, number of policies, claims, and building permit. The analyses are followed by discussions on the regression results.

4.5.1. Flood Insurance Market Penetration

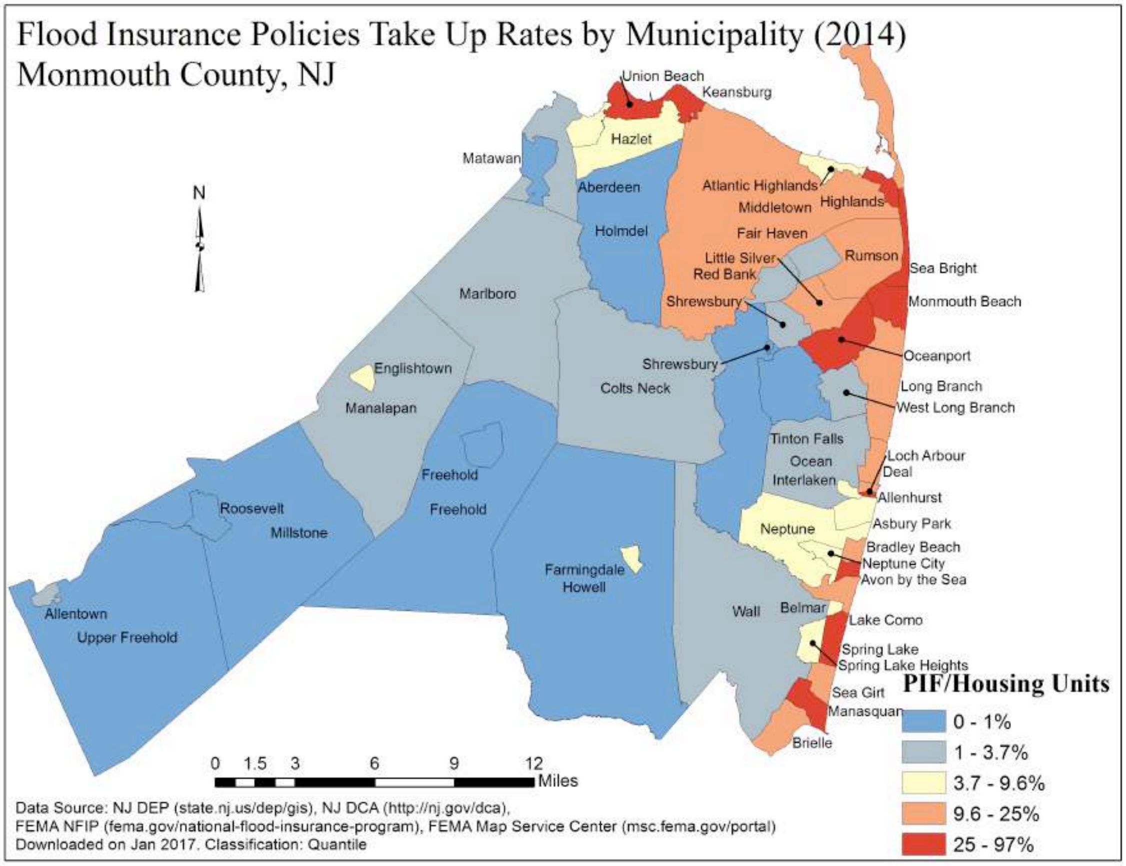
Flood insurance market penetration rate is measured by dividing the total number of residential policies-in-force in any municipality by the number of housing units in the municipality. Figure 4.3 shows that in the period 2010-2014, the top five municipalities with the highest take up rates for flood insurance policies were Sea Bright (95%- 100%), Monmouth Beach (92%-95%), Union Beach (52%-54%), Manasquan (43%-46%), and Keansburg (40%-47%).



Data source: FEMA NFIP, U.S. Census American Community Survey

Figure 4.3: Flood insurance market penetration by municipality in Monmouth County, NJ for the period 2010-2014

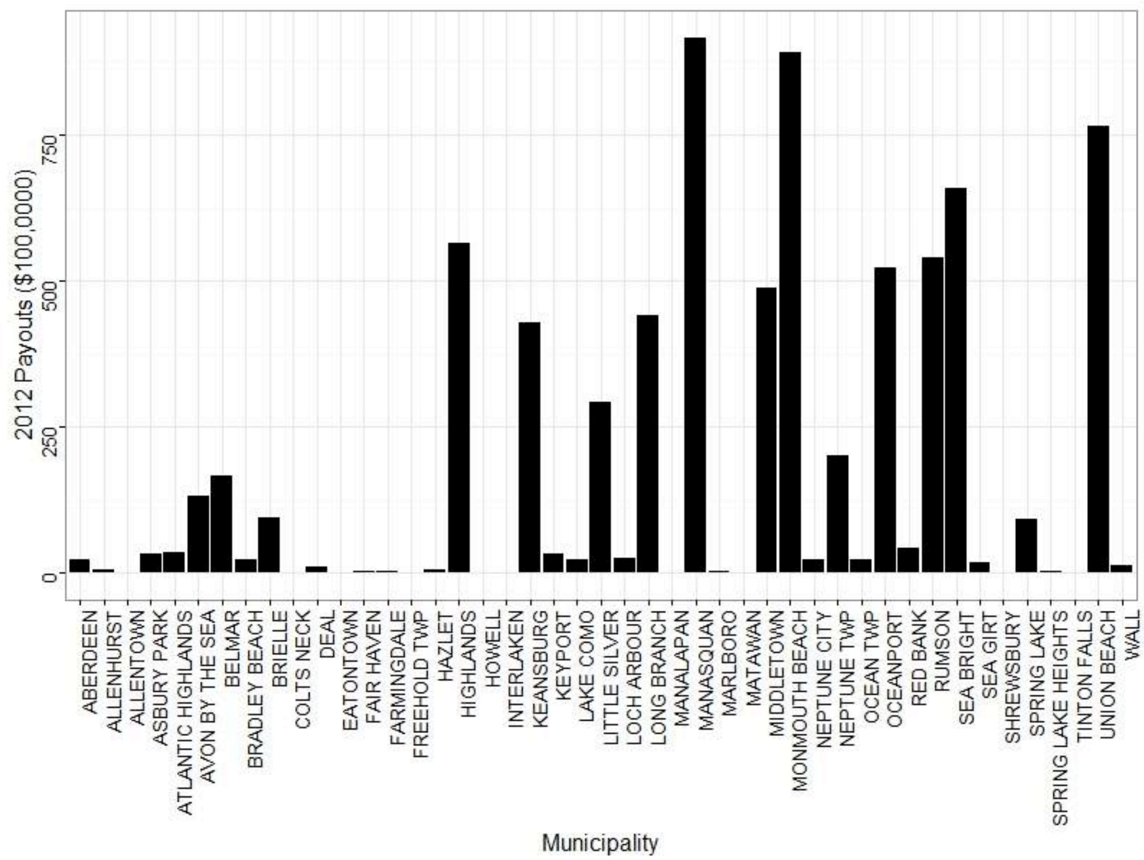
As illustrated in Figure 4.4, the communities with high take up rates in the flood insurance policies are mostly located in coastal regions. In other words, purchase of flood insurance penetrates better in the coastal real property markets than those inland.



Data sources: FEMA NFIP, NJDEP, NJ DCA FEMA Floodplain maps

Figure 4.4: Flood insurance market penetration by municipality in Monmouth County, NJ in 2014

Coastal communities in Monmouth County, NJ were greatly affected when Hurricane Sandy hit the region in 2012. This immediately increased the amount of flood insurance payouts that were paid to the insured homeowners. The top five municipalities with the highest amount of payouts in 2012 were Manasquan (\$91,579,415.30), Monmouth Beach (\$89,204,083.41), Union Beach (\$76,519,131.35), Sea Bright (\$65,798,582.28), and Highlands (\$56,551,612.50) as suggested in Figure 4.5.

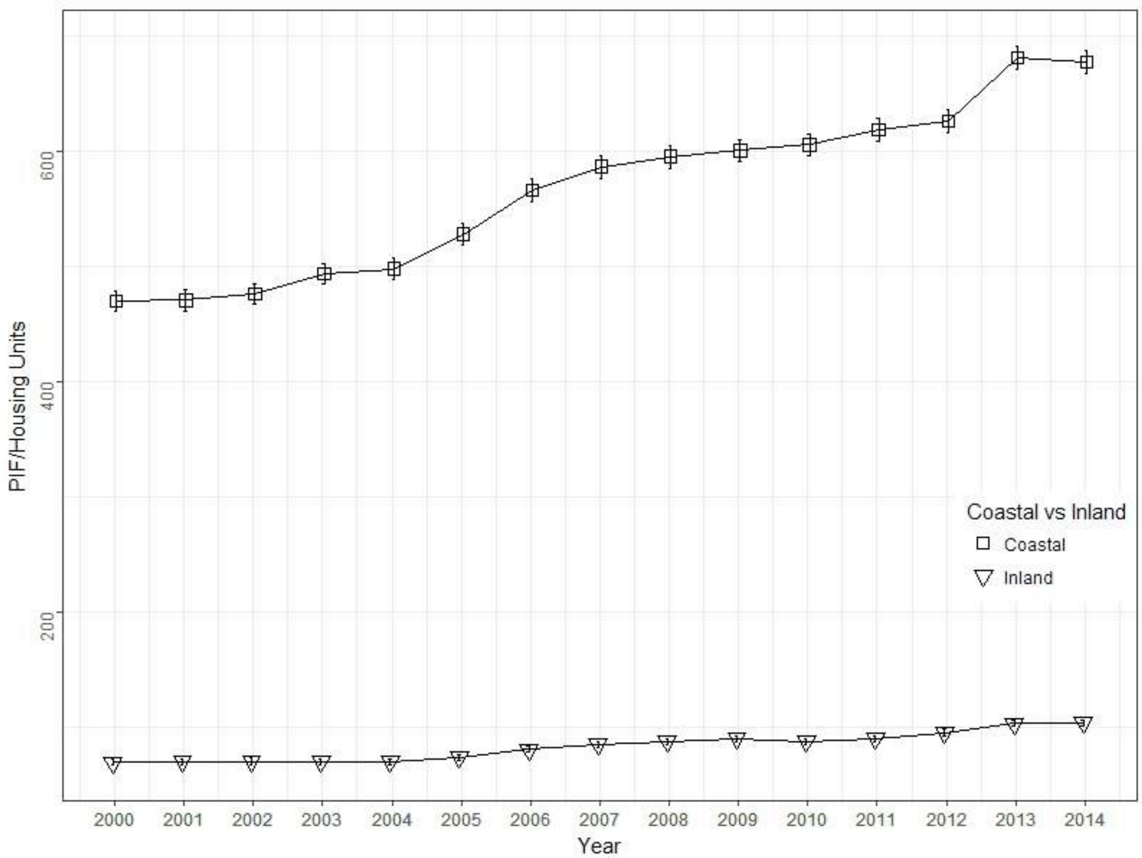


Data source: FEMA NFIP

Figure 4.5: Total Payouts by municipality in Monmouth County in 2012

From Figure 4.3, Figure 4.4, and Figure 4.5, there is a strong relationship between the flood insurance market penetration and the proportion of floodplain areas within a municipality. It seems that coastal towns with large percentage of floodplain areas tend to have high market penetration rates and payouts. Residents of these towns are more aware of the flood risk facing their communities at some degrees. Incentives and other funding sources have been available to the communities that are vulnerable to flood risks. Programs that provide premium discounts like the NFIP's Community Rating System (CRS) have been quite successful in promoting flood insurance purchase to these communities.

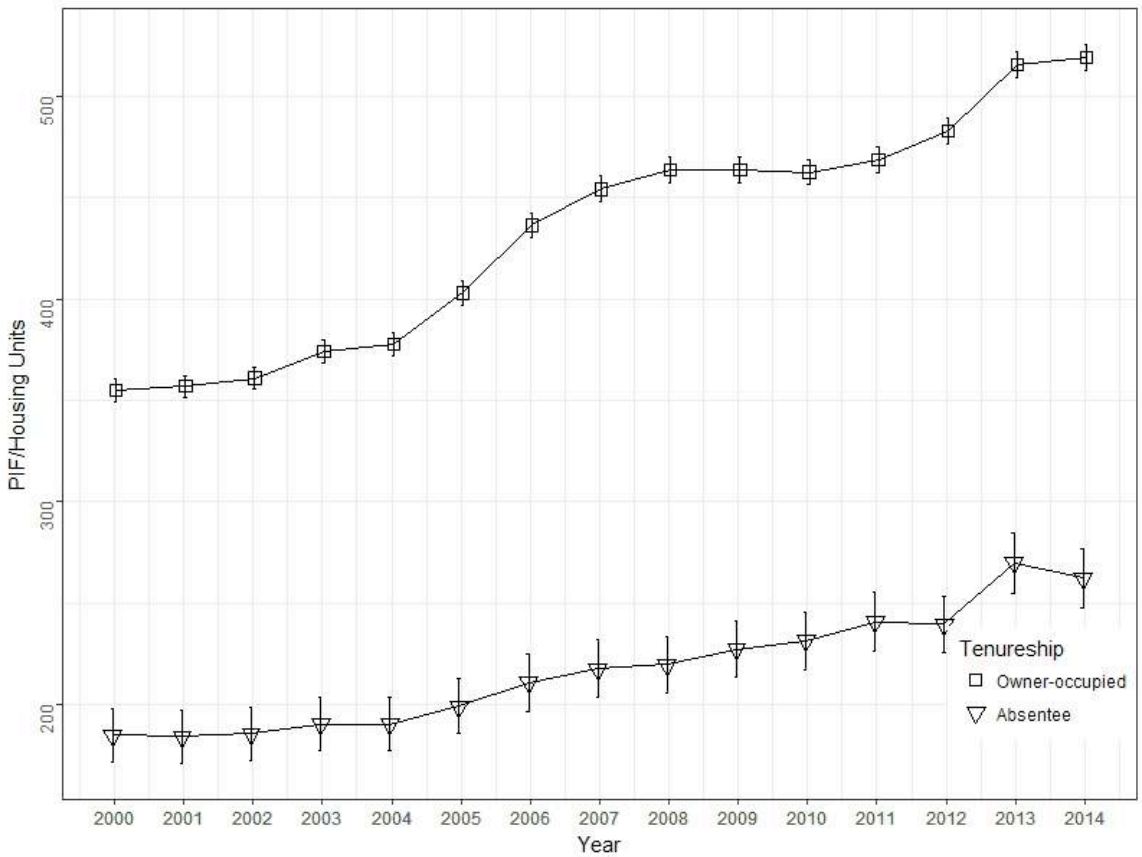
Figure 4.6 illustrates higher take up rates for the flood insurance policies-in-force based on the proximity to the coast. Municipalities that are adjacent to the coastline have greater take up rates than those in inland within the period 2000-2014. For the coastal municipalities, jumps in the take up rates seemed to follow flood events that occurred in the previous years. Hurricane Bill and Hurricane Sandy that made impacts on the New Jersey coast in 2009 and 2012, respectively, have caused significant jumps in the number of policies-in-force by population.



Data sources: FEMA NFIP, NJ DEP

Figure 4.6: Flood insurance market penetration for coastal municipalities and for inland municipalities over the years

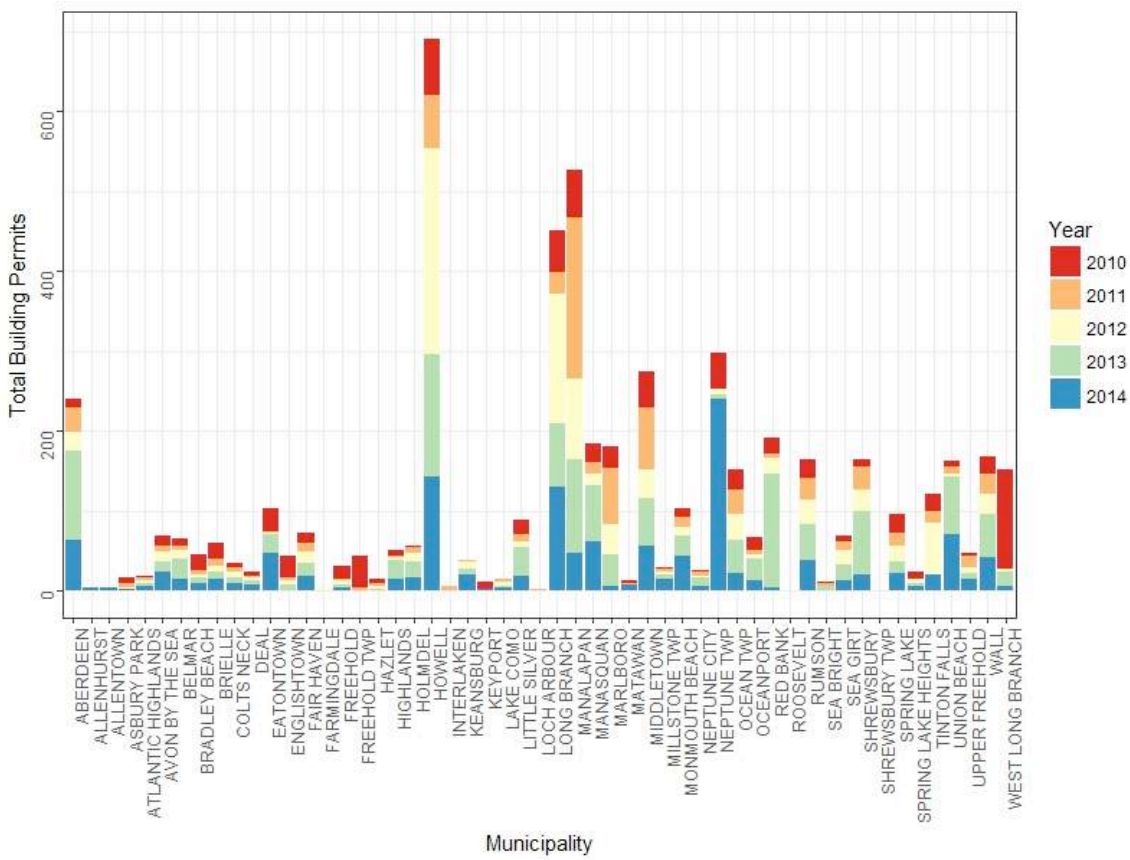
Similar patterns are also seen in the policies take up rates for real properties based on housing tenureship. Figure 4.7 illustrates that municipalities with more owner-occupied properties (larger than 60% of the total real properties) have higher take up rates for policies than those with larger absentee-owner properties over the period 2000-2014. Flood insurance purchase often suggest homeowner's level of awareness of flood risk. It remains a question for psychological research of whether owners who live in the properties are more superior in the risk awareness than those who do not.



Data sources: FEMA NFIP, NJ DEP

Figure 4.7: Flood insurance market penetration for municipalities based on housing tenureship over the years

A great amount of payouts in the aftermath of Hurricane Sandy in 2012 was also followed by a similar trend for the number of building permits issued in that year. As illustrated in Figure 4.8, Howell Township issued the most-number building permits in that year with 258 permits, followed by Long Branch and Manalapan, which each issued 163 permits and 100 permits, respectively. Manasquan and Monmouth Beach, which among the top recipients for flood insurance payouts, issued 15 and 10 building permits, respectively.



Data source: NJ DCA, FEMA NFIP

Figure 4.8: Total building permits by municipalities for the period 2011-2015

Reasonably, there are correlations between the percentage of floodplain areas, the proportion of owner-occupied properties, the number of building permits issued by a municipality, and the amount of flood insurance payouts. Table 4.5 illustrates the top ten performing municipalities based on these categories. Some municipalities are in the top ten position for two or more categories, showing the presence of correlations. Manasquan, as for example, with 58 percent of the areas is floodplain issued 147 building permits and had the highest flood insurance payouts ($91,579,415.3) and on the second position for the amount of flood insurance premiums ($1,877,179). With a score of 66, Manasquan was not among the top ten communities in terms of Community Hardship Index scores (CHI).

Another example is Union Beach. The municipality has large floodplain areas, 87 percent, which made the town suffer much from Sandy and score 70 in CHI. With high participation in the NFIP program, the town paid $1,445,356 for the flood insurance premiums and received insurance claims of $76,519,131.4 in 2012. Between 2012 and 2014, Union Beach was also among the top ten in Monmouth County in terms of building permit issuance, showing that the town has been rebuilding since then.

Also suggested in Table 4.5, Asbury Park, which had 80 percent of absentee-owner properties in 2012, was one of the towns that suffered the most from Sandy (scored 91 in CHI). Since the town did not seem to participate in the NFIP program, Asbury Park was neither among the municipalities with high flood insurance premiums nor those with high insurance claims in 2012.

Table 4.5: A Summary of the top ten municipalities based on the following categories: % SFHA (2012), % owner-occupied properties (2012), building permits issuance (2012-2014), NFIP payouts (2012), PIF/Housing Units (2012), Premium amount (2012), and Sandy Community Hardship Index—CHI (2012)

Rank	% SFHA	% Owner-Occupied	Permits	Claims	PIF/ Housing Units	Premiums	Sandy CHI
1	Sea Bright (93%)	Asbury Park (20%)	Howell (554)	Manasquan ($91,579,415.3)	Sea Bright (0.95)	Middletown ($2,158,677)	Rumson (99)
2	Keansburg (87%)	Long Branch (42%)	Long Branch (372)	Monmouth Bch ($89,204,083.4)	Monmouth Bch (0.93)	Manasquan ($1,877,179)	Asbury Park (91)
3	Union Beach (87%)	Bradley Beach (43%)	Manalapan (265)	Union Beach ($76,519,131.4)	Union Beach (0.53)	Long Branch ($1,575,352)	Shrewsbury Twp. (87)
4	Monmouth Bch (65%)	Red Bank (47%)	Neptune Twp. (252)	Sea Bright ($65,798,582.3)	Manasquan (0.44)	Keansburg ($1,542,667)	Allenhurst (78)
5	Loch Arbour (63%)	Belmar (49%)	Aberdeen (176)	Highlands ($56,551,612.5)	Highlands (0.37)	Highlands ($1,494,572)	Long Branch (72)
6	Manasquan (58%)	Shrewsbury Twp. (49%)	Red Bank (166)	Rumson ($53,875,778.8)	Loch Arbour (0.36)	Monmouth Bch ($1,464,519)	Millstone Twp. (72)
7	Highlands (51%)	Farmingdale (51%)	Middletown (152)	Oceanport ($52,133,254.0)	Spring Lake (0.33)	Union Beach ($1,445,356)	Belmar (71)
8	Avon by the Sea(48%)	Keyport (52%)	Manasquan (147)	Middletown ($48,789,202.3)	Oceanport (0.3)	Sea Bright ($1,197,090)	Union Beach (70)
9	Belmar (39%)	Freehold (54%)	Union Beach (147)	Long Branch ($44,197,470.3)	Avon by the Sea (0.28)	Oceanport ($772,214)	Monmouth Bch (70)
10	Rumson (34%)	Sea Bright (55%)	Shrewsbury (126)	Keansburg ($42,801,090.6)	Rumson (0.22)	Rumson ($727,008)	Avon by he Sea (69)

Data source: U.S. Census, NJ DEP, NJ DCA, FEMA NFIP, NJ Databank

4.5.2. Regression Results

To investigate the performance of flood insurance market, the analysis is divided into two levels. At the municipality level, the analysis uses Equation (1) to estimate the take up rates for flood insurance policies (ln(PIF_HOUSING)). At the property level, the analysis estimates the amount of claims (ln(CLAIMS)) as suggested in equation (2). It is noticed that both dependent variables are log transformed in order to minimize heteroskedasticity in the models. Both PIF/Housing Units and CLAIMS variables are positively skewed with long right tails.

Table 4.6 reports the regression results for estimating the flood insurance policy purchase before and after Hurricane Sandy made a landfall. While Model (1) uses data for the period 2000-2014 with a sample size of 724 policies, Model (2) only uses data for flood insurance purchase before Sandy (2000-2011) with a sample size of 578 policies. One main analysis is to test whether the number of issued building permits (BLDGPERMIT) estimates the policies-in-force take up rates given a flooding event. The analysis also considers its interaction term with the percentage of floodplain areas (SFHAPCT). Model (1) includes an additional variable of Sandy's household hardship index—HHI (SANDY_HHI) and its interaction term to identify the effect of Hurricane Sandy. In both models, the price of flood insurance policy (NFIPPRICE) shows a negative sign and 1% significance for the coefficients, suggesting the price and quantity-demanded relationship in the demand function of flood insurance policy. While race does not have a significant effect on the policies take up rates within a municipality, the average household income (INCOME) negatively estimates the purchase. Although the effect of INCOME is small on the flood insurance purchase, the negative sign for the coefficient has several possible explanations. One is that homeowners in the higher income levels are not really aware of flood risk. Another could be because their homes are not in high flood risk areas after all.

Model (1) of Table 4.6 also shows that the percentage of owner-occupied properties (OWNERPCT) estimates the number of policies-in-force per-total housing units as suggested in a positive significant sign on its coefficient value. Vacant homes also seem to have higher take-up rates in the flood insurance policies, though the effect is small, as suggested by a negative and significant coefficient for OCCUPIEDPCT. In Model (2), housing tenureship variable is not significant in estimating the insurance policy purchase, though it shows a negative sign on its coefficient. The percentage of floodplain areas (SFHAPCT) and number of permits (BLDGPERMITS) are also significant predictors in the model as shown in both positive and negative signs for their coefficient values. Further, there is a positive and significant effect in the flood insurance policies take-up rates based on the interaction of proportion of floodplain areas and building permits, (SFHAPCT*BLDGPERMIT). This suggests that the more building permits issued for floodplain properties, the larger the increase in the aggregate flood insurance purchase within a municipality. Finally, Model (1) shows that Hurricane Sandy affects the flood insurance policy purchase as shown by a positive and significant coefficient for SANDY_HHI. Although small, a similar effect is also seen in its interaction term of (BLDGPERMIT*SANDY_HHI), suggesting that building permits issued after Sandy explain the increase in the flood insurance purchase in any town. The R-squared values for the two models show the overall fit of the models. Model 1 has a R-squared value of 0.841 and Model 2 has a R-squared value of 0.832.

Table 4.6: Regression results from difference-in-differences (DD) model for analysis at the municipality level. Dependent variable is a log-transformed variable of PIF/housing units

	Model (1)	**Model (2)**
(Intercept)	1.1069967422** (0.4705674566)	2.3857805487 *** (0.4328725950)
NFIPPRICE	-0.0000003769*** (0.0000000669)	-0.0000004322 *** (0.0000000744)
AGE25PCT	0.0014888905* (0.0008046607)	0.0012878002 (0.0011438931)
AGE65PCT	0.0480399194*** (0.0062595748)	0.0488115394 *** (0.0072307326)
BLACKPCT	0.0036859878 (0.0034785947)	0.0066126487 * (0.0038809381)
INCOME	-0.0000050197*** (0.0000009977)	-0.0000047060 *** (0.0000011273)
OWNERPCT	0.0096952195*** (0.0022105957)	0.0053322833 ** (0.0023815951)
OCCUPIEDPCT	-0.0346387149*** (0.0032094879)	-0.0317724464 *** (0.0038476149)
SFHAPCT	4.3415508853*** (0.1655114633)	4.6940716318 *** (0.1657474322)
BLDGPERMIT	-0.0109519261*** (0.0027695823)	-0.0044641328 *** (0.0007381192)
SFHAPCT*BLDGPERMIT	0.0258088113*** (0.0051454789)	0.0399935083 *** (0.0063420688)
SANDY_HHI	0.0255965496*** (0.0051683182)	
BLDGPERMIT*SANDY_HHI	0.0001351725* (0.0000529010)	
R-squared	0.809	0.802
Num. of Obs.	724	578

Significant Codes: *** p<0.01, ** p<0.05, * p<0.1

Table 4.7 reports the estimation results by comparing the results from using the fixed-effects model, Model (3), with those from the random-effects model, Model (4).

Both models have 204 observations for the sample size. The resulting fixed effects model support the hypothesis that income (INCOME), property value (PROPVALUECAPITA), population with age 25 year-old and above (ABOVE25PCT), percentage of floodplain (SFHAPCT), and a dummy variable of coastal municipality (COAST) show a positively significant effect in explaining the flood insurance purchase at 5% significance level. The cost per thousand dollars of flood insurance coverage (NFIPPRICE) and percentage of owner-occupied properties (OWNERPCT) negatively influence flood insurance purchase decision. Resulting regression using random effects show only NFIPPRICE and SFHAPCT variables significantly influence the decision to buy insurance. The Hausman test, however, indicates that fixed effects regression results in a better outcome than the analysis that uses random effects, with p-value <0.000. Model 3 performs better than Model 4 in terms of R-squared with 0.806 and 0.489 in values, respectively.

Table 4.7: Regression results for analysis at the municipality level. Dependent variable is a log-transformed variable of PIF/Housing Units

	Model (3)	**Model (4)**
(Intercept)	-0.464494025	2.050723684**
	(0.811490342)	(0.677427991)
log(NFIPPRICE)	-0.020802945**	0.005996356**
	(0.009847066)	(0.002226602)
INCOME	0.000004287**	-0.000000492
	(0.000002061)	(0.000000500)
OWNERPCT	-0.00670724*	-0.003705158
	(0.003466872)	(0.006224340)
PROPVALUECAPITA	0.000000688***	0.000000235
	(0.000000143)	(0.000000144)
AGE25PCT	3.577592452***	-0.311228073
	(1.075026795)	(0.603981976)
SFHAPCT	0.047501509***	0.047350341***
	(0.002720282)	(0.005257600)

COAST	0.380433003** (0.136715571)	0.890775868 (0.252462650)
R-squared	0.806	0.489
Num. of Obs.	204	204

Significant Codes: *** p<0.01, ** p<0.05, * p<0.1

At the property level, results of estimation of equation (2) of three models are illustrated in Table 4.8. The total number of observations for all three models is 6,225 claims. Across the three models, structural attributes have either positive or negative effects in predicting the amount of claims. The number of rooms, square feet, availability of certain structural attributes such as dormer, dock, patio; give positive and significant effects on the total payouts. The height of the structure, building age, total acreage, concrete block foundation, concrete pour foundation, pierpil foundation, and presence of deck and basement negatively influence the total payouts. Post FIRM properties (coded with POSTFIRM) also negatively affect the total payouts at 0.01 significant level across the three models. Across the three models, the total payouts for absentee-owner properties are greater than those for owner-occupied properties as suggested by a negative sign and significant for the coefficients. As illustrated in Table 4.8, Model (5) and Model (6) show that the closer the real properties to the coastline, the greater the total payouts as suggested by a negative sign for the coefficients. Floodplain properties have greater amount of total claims than those that are not located within the floodplain as suggested in the Model (5) and Model (6).

Results from Model (6) and Model (7) include interaction terms of housing tenureship, OWNEROCCUPIED, with either aggregate floodplain variables of 100-year floodplain (FLDZONAAE and FLDZONVVE) and 500-year floodplain (FP500) or aggregate variables of distance to nearest coastlines (COAST500, COAST1000, COAST2000, COAST3000, COAST4000, COAST5000). In Model (2), a positive sign and 0.01 significance level for the interaction term of (OWNEROCCUPIED*FLDZONAAE) suggests that owner-occupied properties located in the floodplain positively influence the total payouts. Other interaction terms of (OWNEROCCUPIED*FLDZONVVE) and (OWNEROCCUPIED*FP500) show positive influence to the total claims but are not significant. In Model (7), owner-occupied properties that are located in close proximity to the coastlines, positively affect the total claims as suggested by positive signs and 0.01 significance-levels for the coefficients of interaction terms. The Rho and Lambda are positive and significant as indicated in each model.

Table 4.8: Regression results for analysis at the property level. Dependent variable is a log-transformed variable of the amount of claims

	Model (5)	**Model (6)**	**Model (7)**
OWNEROCCUPIED	-.0648576*	-.3809638***	-1.072114***
	(.0361299)	(.1191564)	(.1312296)
ROOMS	.0331234***	.0331193***	.0291715***
	(.0097619)	(.0097598)	(.0098778)
HEIGHT	-.1639162***	-.1628548***	-.1602906***
	(.0389721)	(.0389566)	(.0394603)
SEWER	-.2568238	-.2514927	-.2062079
	(.1710871)	(.1710121)	(.1731452)
WATER	.0554227	.054375	.0486407
	(.1505938)	(.1505373)	(.1526068)
GAS	-.129272	-.1202986	-.1075476
	(.0792367)	(.0794177)	(.0840504)
SEPTIC	.2564235	.2823702	.2909511
	(.2774088)	(.2773636)	(.2821949)

BLDGAGE	-.003006***	-.0030274***	-.0032379***
	(.0008264)	(.0008258)	(.000836)
ACREAGE	-.0001592***	-.0001606***	-.0001817***
	(.000058)	(.0000579)	(.0000587)
SQFT	.0001002***	.000099***	.0001007***
	(.0000123)	(.0000123)	(.0000124)
CONDITION	.0708397	.080957	.0359824
	(.1483609)	(.1482978)	(.1500654)
FCONCBLK	-.1005723**	-.1027538**	-.1119331**
	(.0457525)	(.0457255)	(.046286)
FCONCSLB	.0413763	.0398668	.0374532
	(.0679494)	(.0679046)	(.0687872)
FCONCPOUR	-.172606**	-.1747287**	-.1635023**
	(.0802206)	(.0801713)	(.0811469)
FPIERPIL	-.5000545***	-.5000267***	-.4456393***
	(.1285003)	(.1284137)	(.1300211)
FSTNBRK	.1153925	.116619	.1052375
	(.0874813)	(.0874227)	(.0885481)
hasAC	.1885354***	.1877645***	.1828982***
	(.0388811)	(.0388591)	(.039384)
hasFIREPLACE	-.0038439	-.000602	-.0197714
	(.0545913)	3(.0545644)	(.0552864)
hasDORMER	.1436185***	.1420832***	.14279***
	(.0435414)	(.0435237)	(.044102)
hasDECK	-.0698031**	-.0685444**	-.0482976
	(.033628)	(.0336208)	(.0340523)
hasDOCK	.3053986***	.3073958***	.4894978***
	(.0829874)	(.0831137)	(.0812102)
hasSHED1STY	.0491082	.0488533	.04824
	(.0355905)	(.0355681)	(.0359962)
hasBRICK	-.0118298	-.0081772	-.0436326
	(.0548477)	(.0548342)	(.0556452)
hasBASEMENT	-.3538552***	-.3563579***	-.4306711***
	(.0564624)	(.0564611)	(.0566795)
hasPORCH	.0265128	.0284378	.0280274

	(.0350908)	(.0350737)	(.0355636)
hasPATIO	.0995464***	.1004398***	.1090277***
	(.0363508)	(.0363369)	(.0368031)
hasATTIC	.075373	.0719016	.0503926
	(.1097074)	(.1096556)	(.1110567)
POSTFIRM	-.2521324***	-.2549429***	-.2589501***
	(.0559863)	(.0559509)	(.0566362)
LDCOAST	-.1535726***	-.1497458***	
	(.0188436)	(.0188784)	
FLDZONAAE	.7271122***	.4742016***	
	(.068463)	(.1114693)	
FLDZONVVE	.7333618***	.4874232**	
	(.1538214)	(.1951856)	
FP500	.2414468***	.1164541	
	(.0848766)	(.1597741)	
OWNEROCCUPIED*FLDZONAAE		.3539195***	
		(.1241102)	
OWNEROCCUPIED*FLDZONVVE		.3710078	
		(.2919875)	
OWNEROCCUPIED*FP500		.1874143	
		(.1823175)	
OWNEROCCUPIED*COAST500			1.137356***
			(.1312629)
OWNEROCCUPIED*COAST1000			1.01952***
			(.1347337)
OWNEROCCUPIED*COAST2000			.8537486***
			(.1365329)
OWNEROCCUPIED*COAST3000			.57214***
			(.169711)
OWNEROCCUPIED*COAST4000			.3406984
			(.2475238)
OWNEROCCUPIED*COAST5000			.5430697*
			(.3046604)
_CONS	10.33701***	10.54063***	9.840917***
	(.2165714)	(.2287142)	(.1617461)

Lambda	.0773461	.0767598	.1078845
	(.0131179)	(.0131223)	(.0137738)
Rho	2.602715	2.599037	2.518141
	(.1176172)	(.1171716)	(.110195)
Num. of Observation	6225	6225	6225

Significance Codes: *** p<0.01, ** p<0.05, * p<0.1

4.6. Conclusions

The National Flood Insurance Program (NFIP) was created by the U.S. congress in 1968 with a goal to ease the financial burden of government for flood recovery relief. The damage cost paid to the households affected by flooding is supposed to be funded with insurance premiums from policyholders. High intensity climate events, such as the 2005 Hurricane Katrina and the 2012 Hurricane Sandy, placed the NFIP in great debt. The program's current debt has raised concerns regarding its program's financial structure. In order to build a resilient community, the NFIP's policy needs to be studied and improved over time. Whether the NFIP benefits only particular communities and households, and others bear the cost of the program remain a question that motivates this dissertation study. Two levels of analyses are conducted as a response to this question.

The resulting analysis using the case study of municipalities in Monmouth County, shows that both Hurricane Irene and Hurricane Sandy impacted the flood insurance market. Flood insurance purchase increased immediately after large storms, though, no direct impact resulted. Municipalities with a larger proportion of floodplain areas perform well in the number of policies-in-forces by total housing units. Atreya (2013) describes this as an "information effect", in which the availability of FEMA floodplain maps determines the decision, to purchase flood insurance. This accords with the regression results that shows a positive and significant effect of the floodplain variable on the flood insurance purchase. However, a negative and significant effect at the 0.1 level for the housing tenureship variable suggests a low number of policy holders in the municipalities with a larger percentage of owner-occupied properties. The findings also suggest a positive correlation between the flood insurance purchase and the number of building permits issued by municipalities, particularly in the case of coastal towns with significantly larger floodplain areas.

The analysis at the real property level identifies the determinants for the total flood insurance payouts. The resulting analysis shows that most structural attributes significantly affect the amount of claims. Post-FIRM properties tend to have flood risk measures already installed, hence, these properties have lower payouts. The presence of a basement also negatively estimates the amount of claims. Waterfront properties as well as floodplain properties had larger amount of claims. Absentee-owner properties also have higher payouts as suggested in a significant negative sign for the coefficients in the three models. Euclidian distance to the nearest coastline also positively affects the amount of claims. The interaction terms of the housing tenureship variable with either the aggregate floodplain variables or aggregate variables for distance to coast also show significant effects on the total payouts.

Chapter 5

Modeling Coastal Real Estate Market Dynamics using Agent-Based Behavior (ABM) and Econometrics

Abstract

This chapter seeks to test the fifth hypothesis; "Community-level flood risk reduction efforts vary across municipalities and it influences stakeholders' perception on future risks and the actual impact of flooding." With the coupling of econometric analysis and Agent-Based Modeling (ABM), this chapter explores the economic agent behavior in a coastal real property market. The integrated model captures the environmental risk, rational economic actor theories, real estate market theories, and adaptive responses that are reflected in property prices. The model runs on the case studies of two New Jersey municipalities and operates in a realistic GIS landscape of each municipality.

5.1. Introduction

Complex linkages between many urban systems, including environmental, economic, social, and spatial, are subject to many uncertainties and vulnerabilities. One vulnerability includes the impact of extreme climate events on the coastal real property market. Climate researchers have studied the connection between climate change, sea level rise, and hurricanes in recent years. While it remains unclear whether climate change decreases or increases the number of hurricanes, the rising of sea levels is likely to worsen the impact of hurricanes on communities in the future.

The impact of flooding will be more damaging to the real property market. The coastal real property market provides a perfect example of the dynamic relations of market stakeholders affecting environmental and spatial vulnerabilities and vice versa (Webster 2002; Edwards 2002; Godschalk 2003; ULI 2014). The discussion of how resilient a real property market is to extreme climate events has become an important topic (Holling 1973). In the previous ten years, climate related damages have caused US$150 billion losses per year to the real estate industry (ULI 2014). The insurance industry is automatically affected as reflected in the higher premiums and costs charged to homeowners. Increasing extreme climate phenomena and frequent losses also lead to people leaving their communities, thereby affecting the communities' demographic make-up as well as real property value. The real property market, evidently, does not have adequate preparation to anticipate the losses. It is not only the city managers, building code officials, or disaster managers, who are responsible to make their city to be more climate resilient, but also market actors such as real estate investors, developers, and insurance companies must not underestimate the risks related to flooding. Ultimately, it really depends on the capacity and willingness of stakeholders to act, individually and collectively.

Mathematical and economic models have been developed to understand climate-real property market dynamics, and are similarly able to shed light on market stakeholders' actions and interactions. To date, hedonic pricing model is one of many established methods in real property studies. The hedonic model is useful for estimating the tradeoffs for quality attributes of goods and environmental qualities at a given point of time (Palmquist and Smith 2001; Bin 2004; Atreya 2013). However, the hedonic model does not fully detect the non-marginal changes present within the dynamics of real property market. Coastal flooding is one of the extreme climate events that often greatly disrupts the market dynamics. The resulting hedonic function prior to flooding may be different from the resulting hedonic function after flooding.

Studies now show that climate resilience in the real property market depends on a range of social factors such as levels of income, education, age, and awareness of risks. Individual stakeholder adaptations depend on one's perception of risks and choice of response actions. Institutional affiliations creating interactions and self-organizing actions also contribute to resilience strategies within the market. The development of models in recent years accounts for these individual and social behaviors. There is, however, a limited application that is related to climate change and, the accuracy of the models provide still remains a question. Some of these models are agent-based, multi-agent, microsimulation, and other bottom-up approaches (Matthews et. al. 2007; Parker, et. al. 2003; An 2012; Levy et al. 2016).

Agent-based models (ABMs) have been particularly useful in exploring the specifics of abrupt non-marginal changes, such as coastal flooding and the agent adaptive-behavior that emerge over time. ABM assumes that actions performed by the agents, either individually or collectively, shape the attributes and spatial amenities of a real property, thereby, the whole dynamics of the real property market. Therefore, this study takes the strengths of both hedonic pricing model and ABM in explaining the real property market's resilience towards coastal flooding. Specifically, this chapter focuses in understanding the stakeholder behavior in the real property market given the changes in the environment.

5.2. Method

This study integrates an ABM model with the heterogeneity of a property value estimation model, flood insurance model, microeconomic demand/supply model, and individual and collective resilience behavior model. The hedonic property pricing model is utilized for identifying influential factors that estimate the property value and flood insurance purchase. The model of the coastal real estate market is created based on two municipalities in Monmouth County, New Jersey. Parcel map, floodplain map, sales data, and flood insurance data for these two towns are collected from various sources. Data on flood-risk perceptions and mitigation and adaptation strategies are based on previous studies conducted by Monmouth U. Polling Institute (2013), Boulware (2009), and Howard, (2014).

The simulation experiment starts with a spatially explicit parcel model of a city, in which each parcel is attributed with property information, neighborhood characteristics, location characteristics, flood zone characteristics, and flood insurance purchase characteristics. These attributes are updated over time through co-simulation with the ABM model that simulates the stakeholder individual and social behavior. The stakeholders that include government, developer, bank, insurer, homeowners, and homesellers, vary in, and act based on, the roles that are assigned to them.

The development of the model has one main goal that is to explore real property market resilience toward coastal flooding. Therefore, the calibration and validation of the models highlight the importance of planning and policy formation in regard to the real property market. In order to achieve this objective, this chapter adopts the following experimental workflow of: (1) simulate flood-risk awareness and adaptive responses of real property market stakeholders, and the resulting real estate market values; (2) investigate the behavioral effects on other interesting sub-markets such as flood insurance market and real property markets based on tenureship (i.e. owner-occupied and absentee-owner properties); (3) validate the resulting models with real market data from two towns; and (4) explore "what-if" scenarios.

5.3. Cases Studies of Union Beach, NJ and Highlands, NJ

The simulation experiments are based on two municipalities that are located in Monmouth County, New Jersey. They are Union Beach and Highlands, which both were greatly affected by Hurricane Sandy in 2012 (see table 5.1 below). More FEMA assistance to individuals was given to Union Beach(=$5,772) than to Highlands (=$3,711). According to the Household Hardship Index (HHI), Union Beach scored 70, which is higher than Highlands scored at 67 on a scale of 1 (least hardship) to 100 (greatest hardship). Similar scores also apply for these municipalities in terms of the Community Hardship Index (CHI) (see Table 5.1). In 2012, it was only 30 percent of homeowners insured their homes in Highlands and 54 percent homes were insured in Union Beach. In terms of the National Flood Insurance Program Community Rating System (CRS), a voluntary program participated in by communities to reduce flood-risks, Union Beach is in class 6, which make the community eligible for up to a 20 percent discount on their flood insurance premiums. Highlands has not yet participated in the CRS program. The amount of payouts to the Sandy-affected policyholders are higher for Union Beach than Highlands, which shows that the scale of damages caused by Hurricane Sandy between the two municipalities.

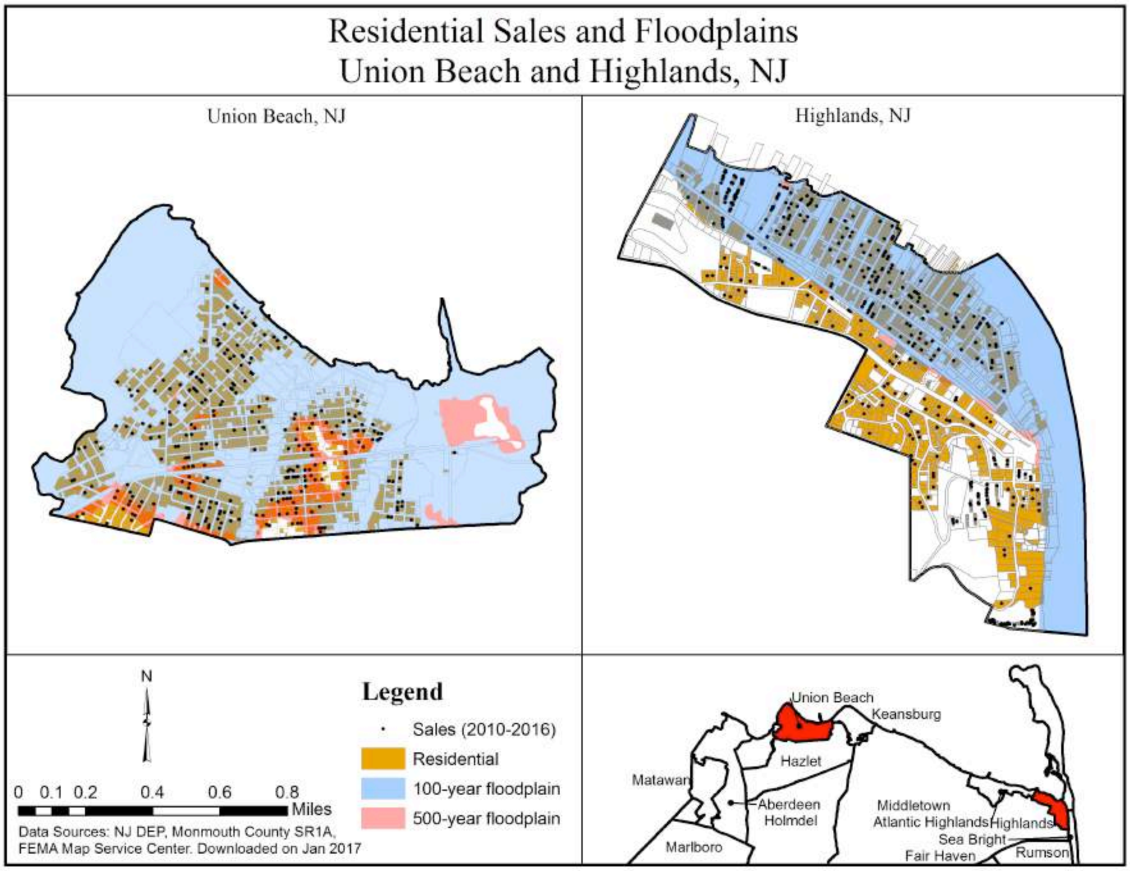
Table 5.1: A comparison metrics for Union Beach and Highlands

	%SFHA	HHI Rank	CHI Rank	Average FEMA IA assistance	No Home Owners Insurance	PIF/ Housing Units	Premium Amounts (millions)	NFIP Payouts (millions)
Union Beach	87% (#3)	19	24	$5,772	46%	0.53 (#3)	$1.4 (#7)	$89 (#3)
Highlands	51% (#7)	29	37	$3,711	70%	0.37 (#5)	$1.5 (#5)	$57 (#5)

Data source: Hoopes Halpin, 2013

In order to develop a more realistic representation of the two towns, data on the municipal demographics is collected to characterize the agents in the simulation. Union Beach is a borough in Monmouth County with a total population of 6,245 and 784 per-square mile in density (U.S. Census, 2010). U.S. Census in the same year also accounts for 2,111 households residing in the borough. The borough has 2,269 housing units with the median house price, $181,898 and 14 percent of the total units is renter-occupied. The demographics include 91.05 percent White, 10.98 percent Hispanics or Latinos, 1.54 percent Black or African American, 0.16 percent Native American, 1.81 percent Asian, and 3.09 percent from other races. Population under the age of 18 were 24 percent of the population, 8.9 percent from 18 to 24, 27.1 percent from 25 to 44, 30.8 percent from 45 to 45, and 9.3 percent were 65 years of age or older. According to the Census's 2006-2010 American Community Survey (in 2010 inflation adjusted dollars), median household income was $61,347. 33 percent of households have an income below the ALICE threshold. Geographically, it has 4.51 percent of water area of a total area of 1.889 square miles and located at average of 3 feet above sea level. The borough that was incorporated on March 16, 1925, and borders municipalities of Hazlet, Keansburg, and Keyport, which all are in Monmouth County.

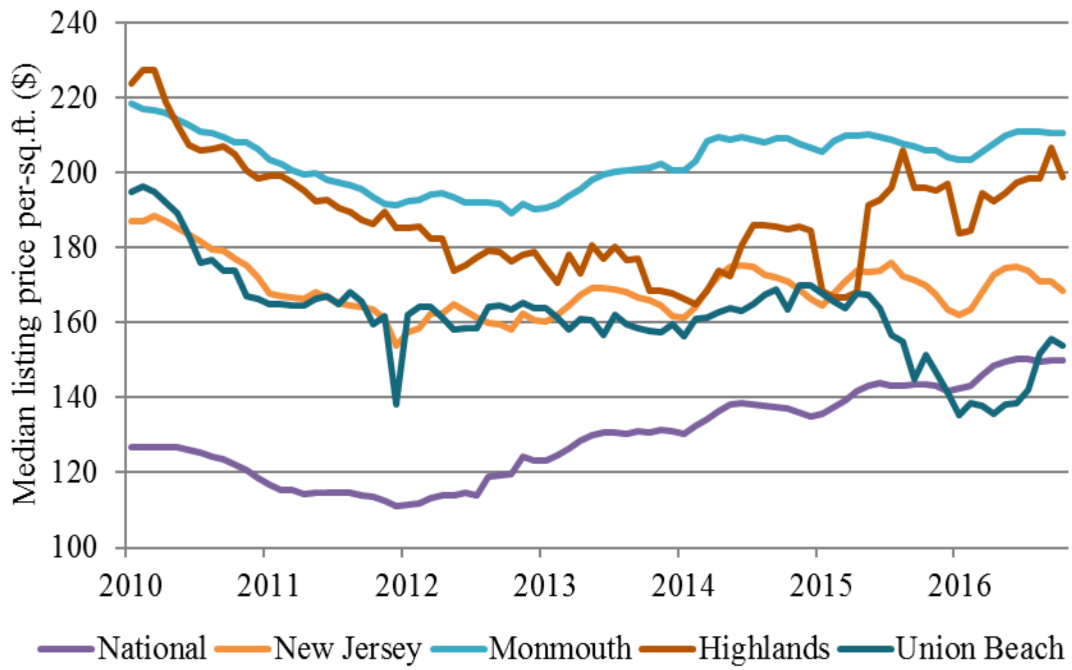
Only 11 miles eastward from Union Beach, Highlands is a borough that overlooks Sandy Hook and the Atlantic Ocean with larger water areas, 43.96% of the total area of 1.369 square miles, and located 13 feet on average above sea level. The borough was incorporated 25 years earlier than Union Beach, on March 22, 1900. According to the 2010 U.S. Census, the borough's population was 5,005 and 709 per-square mile in density. The demographics of the borough did not show much difference from Union Beach. The racial makeup was 92.97 percent White, 6.47 percent Hispanics or Latinos, 1.62 percent Black or African American, 0.28 percent Native American, 1.30 percent Asian, and 1.94 percent from other races. In the borough, 14.2 percent of the population were under the age of 18, 6.6 percent from 18 to 24, 29 percent from 25 to 44, 37.3 percent from 45 to 64, and 12.9 percent were 65 years of age or older. The median household income was slightly higher than Union Beach Borough had at $89,415, adjusted to 2010 dollars (U.S. Census's 2006-2010 ACS). The borough is a home of 7,225 households, residing in 7,418 housing units, which 9 percent of them are renter-occupied. The median house price is $235,653, which is higher than in Union Beach. Figure 5.1 illustrates the sales for both towns during the periods 2010-2015. It also shows that a number of sales were located within the 100-year floodplain. Union Beach has a greater floodplain areas than Highlands does as suggested from Figure 5.1.



Data Source: NJ DEP, Monmouth County SR1A, FEMA Service Center

Figure 5.1: Residential property sales and floodplain maps for Union Beach and Highlands, NJ (2010-2015)

As indicated in the above paragraph, the median listing property prices in Highlands are higher than those in Union Beach for the period 2010-2016. Figure 5.2 illustrates the listing price per-square feet for both towns. The median property price per-square feet dropped after Hurricane Sandy. The effects were temporary before the prices returned to the rate before Sandy in only within a year or two. While Highlands's property prices per-square feet showed an increasing trend, prices of Union Beach's properties decreased between 2015 and 2016.



Data source: Zillow Research Data

Figure 5.2: Median listing price per-sq.ft for the period 2010-2015

Calibrating and validating the ABM model can be challenging since the model maximizes the assumption about real property market by relying much on the empirical data and limited use of stochastic variables (Levy, 2016). Therefore, real data on the physical and demographic characteristics of the towns are used in the model's calibration and validation process.

Table 5.2 shows flood insurance data on the total payouts, amount of collected premiums, and number of policies are the estimated variables. Like many other towns that were hit by Hurricane Sandy in October 2012, the amount of flood insurance payouts for these towns spiked and exceeded the premiums accumulated over the years due to the storm surge damages caused by the coastal flooding. From the same table, it is noticed that although Union Beach has more policies-in-force than Highlands has, the amount of premiums collected from Union Beach is slightly lower than those from Highlands, indicating that participating in the FEMA CRS gives premium discount to the Union Beach's policy holders. In terms of the amount of claims caused by Sandy, Union Beach is greater than Highlands by $16,300,611. This is because Union Beach has a larger floodplain areas (86.7%) than Highlands (51.2%).

Table 5.2: Total Payouts, Collected Premiums, and Number of Policies-in-force for the two towns for the period 2000-2014

	Highlands			**Union Beach**		
Year	**Claims Amount**	**Collected Premiums**	**Policies-in-force**	**Claims Amount**	**Collected Premiums**	**Policies-in-force**
2000	$0	$424,602	872	$0	$510,120	987
2001	$0	$446,790	900	$1,758	$539,408	1,008
2002	$0	$521,735	934	$5,789	$605,049	1,051
2003	$0	$598,170	958	$0	$647,020	1,059
2004	$0	$677,793	973	$4,454	$695,954	1,080
2005	$53,306	$786,112	1,052	$21,584	$764,453	1,088
2006	$1,627	$866,116	1,076	$0	$850,381	1,100
2007	$6,602	$1,007,396	1,108	$18,494	$980,752	1,127
2008	$0	$1,169,151	1,088	$7,844	$1,081,268	1,135
2009	$0	$1,247,751	1,088	$7,125	$1,170,548	1,156
2010	$84,775	$1,341,614	1,112	$710,990	$1,283,496	1,173
2011	$4,557,490	$1,420,880	1,181	$549,723	$1,330,254	1,173
2012	$49,735,726	$1,494,572	1,160	$66,036,337	$1,445,356	1,195
2013	$0	$1,618,235	1,216	$2,242	$1,484,063	1,236
2014	$0	$1,652,342	1,168	$0	$1,442,760	1,219

Data source: FEMA NFIP

5.4. Simulation Model

This section describes a workflow of the proposed ABM model. It will start with an explanation on the overall modeling framework and followed by a discussion on the sub-models that are included in the ABM model. Then, a discussion on agents will follow in the next sub-section, which each represents a stakeholder in the actual real property market. To test the overall modeling logic of the proposed ABM model, a set of scenarios and its combinations are constructed and discussed in the following sub-section.

5.4.1. Modeling Framework

The components and details of ABMs are commonly developed in stages. Buchmann et al. (2016) uses the method in developing an ABM model of residential mobility, which includes adding the heterogenous agents, the decision model structure, and the usage of input data and information. In this dissertation, the proposed ABM model is a scaled-up of Handi's 2015 model that model of the stakeholder behavior and interaction in the coastal real estate market in Monmouth County, New Jersey. The proposed ABM model does not only consider the modeling elements that are useful for calibration and validation purposes but also sub models that constitute a more realistic representation of the real property market. As illustrated in Table 5.3, the sub-models include: (1) spatial model that is created using GIS; (2) hedonic property pricing model; (3) flood insurance model; (4) double auction market model.

The proposed ABM model includes significant additions that were not previously included in Handi's 2015 model, including the sea-level data and the spatially explicit data. While sea-level data describes the flooding events over the years, the spatial data gives characteristics not only to each property parcel environment such as whether the property is located in the floodplain or not, but also the neighborhood attributes and the structural attributes of the property. Another additional component of the ABM model includes a more detailed flood insurance component that is developed based on the FEMA National Flood Insurance Program (NFIP). Several types of flood insurance premium discounts such as through the CRS participation and deductibles, as well as the mandate for flood insurance purchase fall under this component category.

Table 5.3: A summary of the proposed ABM model components and details

Components/ Sub-models	**Description**
Heterogenous agents	All household agents are heterogeneous and calibrated with various data sources (i.e. U.S. Census data).
Spatial data	All parcel and house agents are heterogenous and calibrated with data sources, including New Jersey Tax Map, CAMA data, MOD IV data, and U.S. Census block/block groups data, and FEMA flood zones data.
Sea level	Time series data of sea level is collected from National Oceanic and Atmospheric Administration (NOAA).
Double auction market	Double Auction Market is a trading decision model that is created based on Gode and Sunder (1993).
Flood insurance	Flood insurance model is a more realistic representation of the National Flood Insurance Program (NFIP) and the flood insurance market. The model includes components, such as types of premium discounts (i.e. deductibles, Community Rating System-CRS, Grandfathering, preFIRM) and other related such those in Biggert-Waters 2012 and NJ Blue Acres Buy Out.
Hedonic property pricing function	Hedonic property pricing model is a property value estimation model that is commonly used by appraisers and developers. By using R-extension for NetLogo's capability, the model performs a robust co-simulation of the stakeholder behavior model and hedonic pricing function.

Similar to Handi's 2015 model, the proposed ABM model is also programmed in NetLogo (Wilensky, 1999; Tisue and Wilensky, 2004). NetLogo is an open-source software for simulating natural and social phenomena, which includes agents interacting to one another and . NetLogo enables the implementation of several decision mechanisms. As described in Table 5.3 above, homeseller-agents and developer-agents estimate the property price by running a hedonic property pricing function implemented through a co-simulation the NetLogo programming environment with R programming environment. Section 5.4.2. below describes the co-simulation process in detail. Homowners' decisions to adapt to flood risk such as to repair, to elevate, or to sell are calibrated against empirical data that is provided by the Monmouth University Polling Institute through a series of household surveys that was previously conducted in 2012 and 2013. Other decision mechanisms implemented within the NetLogo include the investment choices either to purchase or to rent properties, the decision for homeowners to purchase flood insurance policies and to follow their neighbors' actions. The proposed model also keeps decision mechanisms related to the double auction market from Handi's 2015 model, which include the home sellers' setting on ask-price, home buyers' setting on bid-price, and transaction price. For calibration and validation purposes, the model runs each case town (e.g. Highlands and Union Beach) separately based on the parameters that characterize the towns.

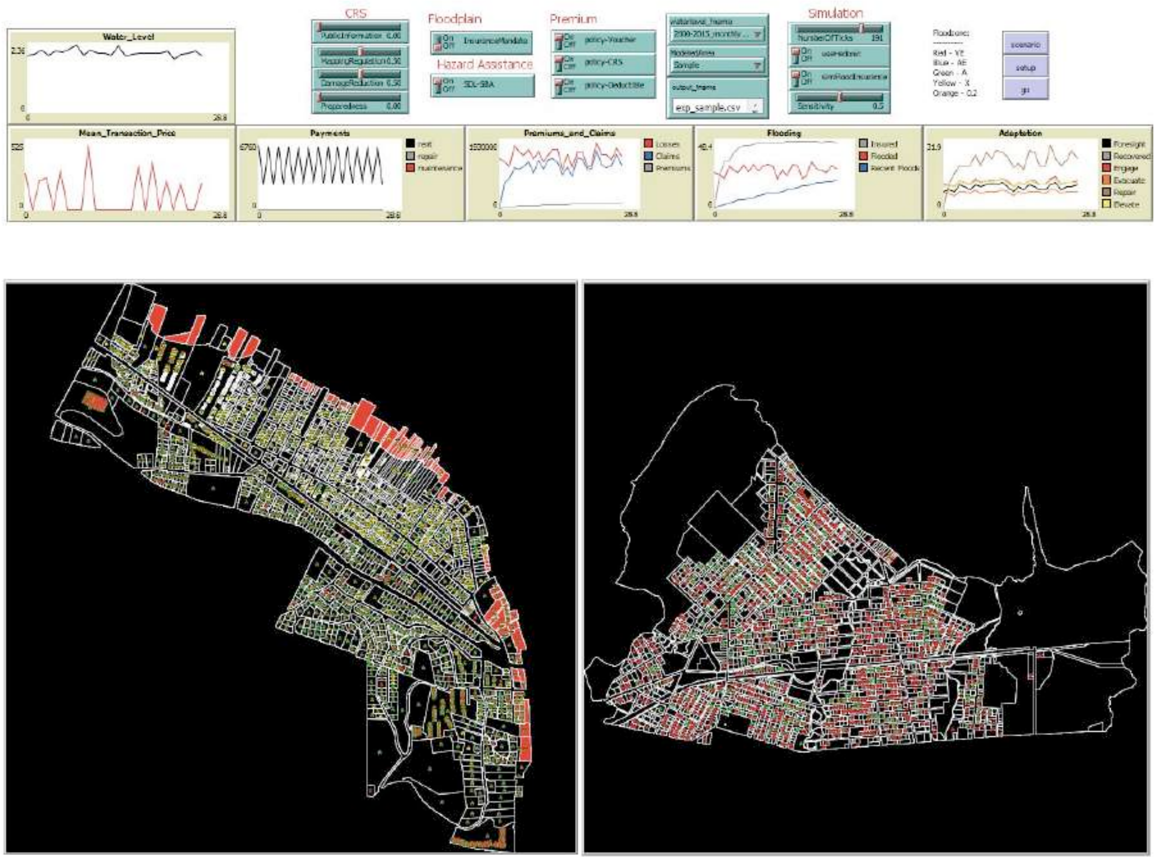


Figure 5.3: NetLogo software interface that simulates the real property market and resilience in Highlands and Union Beach in New Jersey

5.4.2. Hedonic Pricing Model using NetLogo R-extension

In the ABM model, homeowners, who decide to sell their houses, set their initial ask price by consulting with the developer. Like in the real world, developers estimate the value of a property by performing the hedonic pricing analysis to identify the influential property attributes. This is a more advanced approach than Handi's 2015 model, in which the ask price is based only on the price the sellers paid when they bought the house and the market price at that time. As shown in Table 3.1 in Chapter 3, there are multiple characteristics and attributes that significantly estimate property value. These attributes include neighborhood characteristics that are collected from census (e.g. median household income, education levels, ages), location characteristics (distance to nearest coastline, rail station, police station, and school), flood zones characteristics, property structure characteristics (e.g. number of rooms, building age, square feet, availability of air conditioning, availability of amenities--sewer, water, gas, air-conditioning, fireplace, dormer, deck, dock, pool). This research uses the same set of factors to determine flood insurance purchase in the model. Hedonic pricing model is implemented within an R-environment. NetLogo co-simulates with the R-environment by calling an R-extension. A developer-agent sends a request through the R-extension within NetLogo and receives coefficient-values that correspond to each attribute. The developer-agent uses these coefficients for estimating the value of a property. Sub-section 5.4.5 Agents below explains the developer-agent modeling logic.

5.4.3. Flood Insurance Model

A more explicit flood insurance model is also developed for this study that includes realistic flood insurance rates, discount rates, and adaptation funding opportunities. Premium rates for floodplain properties are higher than rates for properties located outside the floodplain. Properties with basements also typically, have higher rates than those without. Discounts for flood insurance rate premiums also apply in various ways, such as: (1) to any property that was built before the release of FEMA flood map in 1974 (referred to as pre-FIRM properties); (2) through deductibles that are higher for any property that is flood insured with coverage above $100,000 than those with below $100,000; (3) to any property located in a town that participates in the Community Rating System (CRS) (i.e. Union Beach, NJ); (4) through a voucher (Kousky and Kunreuther 2013) that applies to any property located in either flood zone A and V; (5) through other means of mitigation strategies like elevating the property. In the aftermath of flooding, homeowners may also request for loans through the Subsidized Disaster Loan from Small Business Administration (SBA).

5.4.4. Double Auction Market

The model also has a multi-agent system (MAS) component, which presents stakeholder interactions occurring in the marketplace. This study adopts a double-auction market concept to model the interaction between homebuyers and home sellers. The double-auction market concept was firstly developed by Gode and Sunder (1993). In the model, developers and homeowners are the property sellers. People look for homes by considering 30 houses before deciding either to purchase or to rent the desired house. The double-auction market only applies for houses being sold by homeowners, where home buyers make bids and home sellers adjust their ask prices until a transaction price that is equal to the earlier of the two, results. Initially, homebuyers bid based on the affordability of houses, which is 30% of their annual income (FHA 2014), and homesellers ask for a price that is recommended by the developers (see section 5.4.2 above). Throughout the transaction process, there are four possible states: (1) when there is no best ask (lowest ask price) nor a best bid (highest bid price); (2) when there is a best ask and no best bid; (3) when there is no best ask but a best bid is present; or (4) when a best ask and best bid are present.

5.4.5. Agents

In the model, six agent types are modeled with individual characteristics and interaction behaviors. These agent behaviors and interactions result in patterns based on insights that are implemented in the real property market and the flood insurance system.

Houses Houses are agents whose information is mainly computed through their interactions with other agents. For example, the attributes and the value of a house is indirectly affected by a flood. Initially, some houses are for sale and the rest are owned by homeowners. The model also incorporates a separate home rental market to accommodate the reality of coastal residential patterns in New Jersey. A real property's attributes and value are calibrated and validated with MOD-IV data and SR1A data provided by the Monmouth County Tax Records office.

Households Households are agents created on the basis of which insight can be gained from real property market. They buy, own, and sell houses. They also insure and perform adaptation strategies against flood risks. People look for their desired homes based on several factors. Figure 5.3 illustrates these factors that are included in the simulation model. They are residential type (i.e. single family or multifamily), square footage, floodplain, proximity to amenities like central business district (CBD) and waterfront. A variable for distance to the nearest CBD is an aggregate distances of related measures that commonly found in the CBD, such as schools, police stations, fire stations, train stations, and bus stations. People decide to either rent or purchase homes based on the affordability of the house. While homerenters' decision mechanisms are not fully modelled, homebuyers enter the marketplace through a bidding process. As illustrated in Figure 5.4, a homebuyer becomes a homeowner of a house, whose seller agrees to sell at the transaction price. Unlike home renters, who may not perform any adaptation strategies, such as purchasing flood insurance; homeowners make the purchase based on several factors. A homeowner maintains the property by paying fees that is termed in either annual basis or one-time. Annual fees may include property tax, mortgage fee, and flood insurance fee. Repair fee and flood control fee are considered as improvement fees that are paid at a one-time basis. Any homeowners, who can no longer pay these fees, would sell the properties. For profit and jobs relocation are some other reasons for homeowners to sell their properties. Sellers form their initial ask price by requesting a price recommendation from real a estate agent. Similar to the real-world real estate market, real estate agent appraises properties with a hedonic property pricing function. The seller-agents interact with the buyer-agents in the modeled real estate market that adopts a double auction market concept (Gode & Sunder 1993). Failing to sell their properties means the homesellers need to adjust the prices asked for the properties on sale.

In the model, household characteristics and behaviors are calibrated with multi-year data collected from U.S. Census' American Community Survey (ACS) data. Households' adaptive behaviors toward coastal flooding are calibrated with data collected through survey activities that were previously conducted by the Monmouth University Polling Institute in 2013 and 2014.

Homebuyer/Homerenter Actions

Homeowner Actions

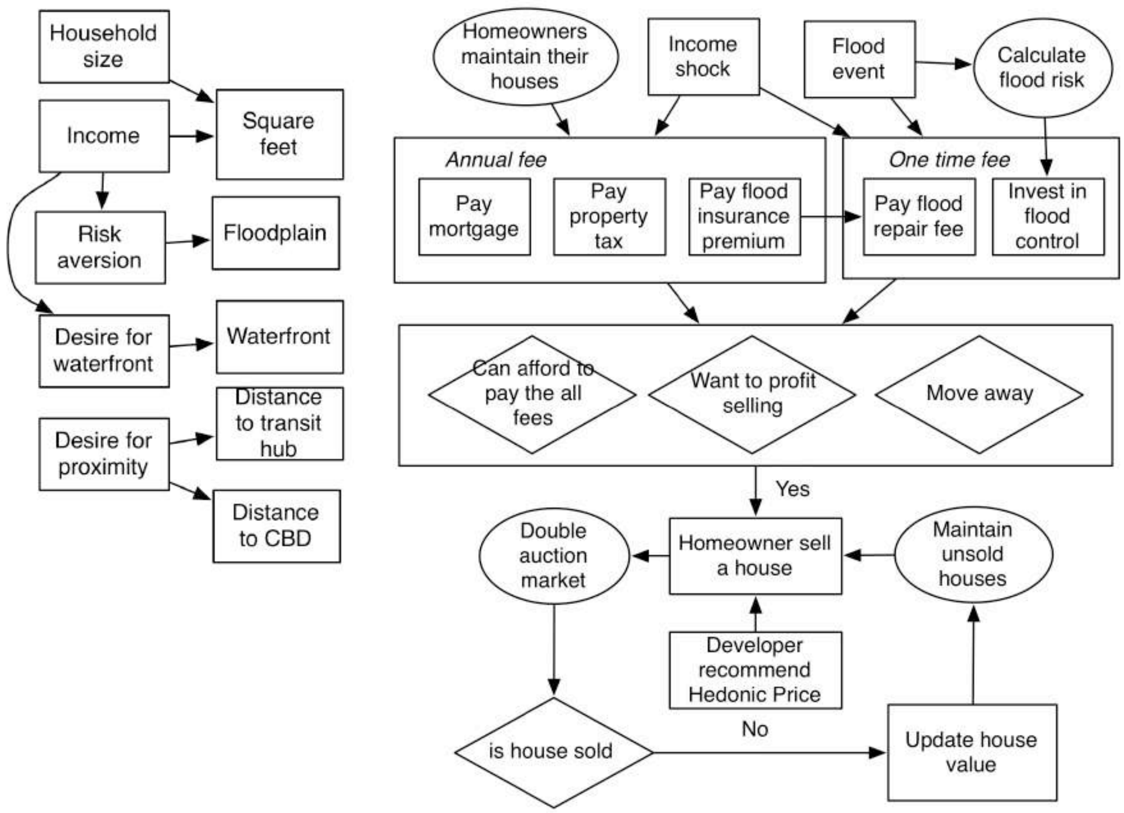


Figure 5.4: Model of household's behaviors

Insurer The insurer is an agent that sells flood insurance policies to homeowners and collects premiums. The insurer, in collaboration with the Federal Emergency Management Agency (FEMA), also maintains the National Flood Insurance Programs (NFIP) by paying insurance claims after flooding. As illustrated in Figure 5.5, this model considers a single insurer agent and some minimal insurance market dynamics. While the model keeps track of its assets, the insurer-agent will never go bankrupt and leave the model environment. The insurer-agent mimics any insurance company work in the real world through collecting premiums from policy holders and compensate at times of loss of their properties due to flooding.

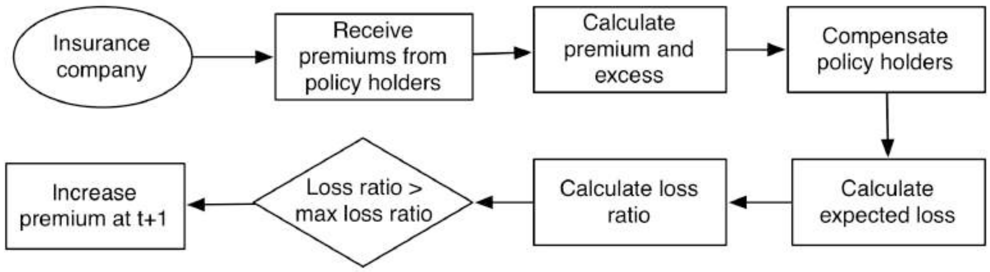
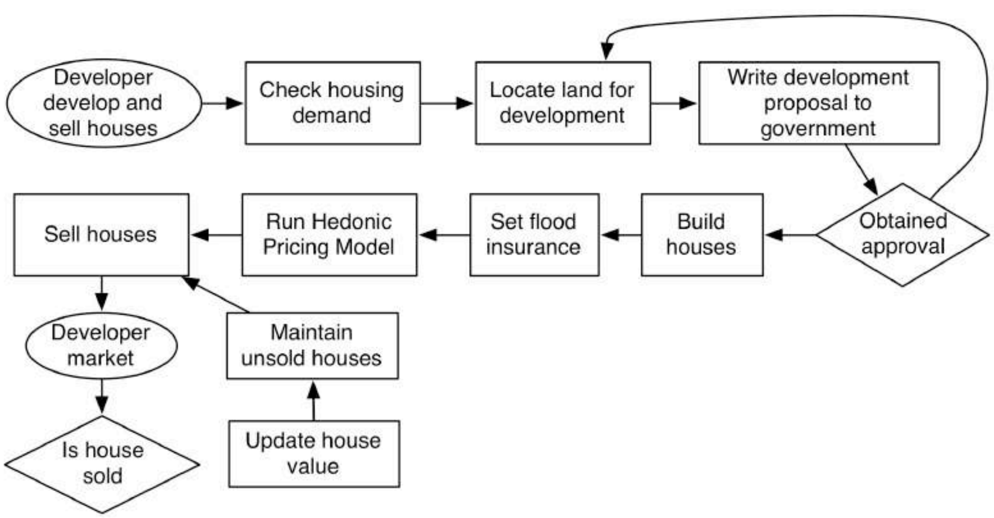


Figure 5.5: Model of insurer's behaviors

Real Estate Agent / Appraiser / Developer In the model, a modeled agent is created to represent three stakeholders, namely real estate agent, appraiser, and developer. As a developer, the agent builds new houses and sells them on the market. As illustrated in Figure 5.6, the developer builds houses by considering the flood risk and asks for a development approval from the government's zoning agent. Houses that are built within the floodplain will be elevated. The agent sells the newly-built houses at the market price and without any bidding process, which means the agent will not lower the price if the house remains unsold. As a real estate agent and/or an appraiser, the modeled agent received requests for price recommendation from home sellers. The agent, then, will run hedonic property price function to adjust the property market price.



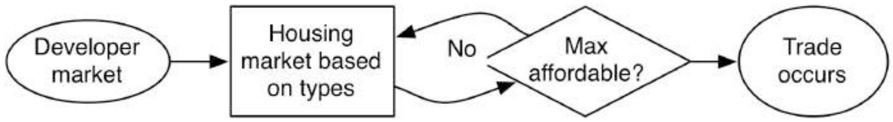


Figure 5.6: Model of developer's behaviors

Bank The bank forecloses houses whose owners can no longer afford to pay their mortgage (and other fees) and decide to put their houses for sale in the market. The bank sells the foreclosed houses.

Local government The local government maintains policies related to the National Flood Insurance Policies, such as building elevation, flood insurance insurance mandate, and premium discount rates. As illustrated in Figure 5.7, a single agent representing local government is also responsible for approving development proposals requested by the developer.

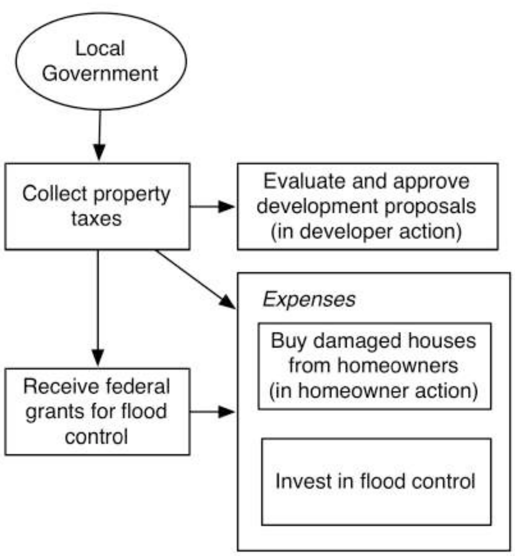


Figure 5.7: Model of local government's behaviors

5.4.6. Simulation Scenarios

The goal of running a simulation experiment is to provide insight on the indirect impact of coastal flood events on stakeholder's perception and adaptive behavior on flood risks. Systematically running the simulation experiment is also useful to test the performance of the ABM model. Therefore, thirty-two simulation scenarios, with each having 5 simulation runs, are developed based on the policy parameters available to initiate the simulation. As suggested in Table 5.4, the model considers the following policy parameters: (1) CRS-participation[9], (2) Flood insurance mandate[10], (3) Elevation mandate[11], (4) Voucher[12], (5) Disaster loans[13]. The simulation scenarios are also developed to test the model components and details that include the hedonic pricing model, double auction market, and flood insurance model.

Table 5.4: Policy scenarios included in the ABM model

Scenario #	CRS	Flood Insurance Mandate	Elevate Mandate	Voucher	Disaster Loans
1	yes	yes	yes	yes	yes
2	yes	yes	yes	yes	no
3	yes	yes	yes	no	yes
4	yes	yes	yes	no	no
5	yes	yes	no	yes	yes

[9] Community Rating System (CRS) is an NFIP voluntary program provides discounts on flood insurance premiums paid by any policyholder whose community meets and recognized for the flood-risk reduction measures.

[10] Flood Insurance Mandate requires homeowners whose properties located in the floodplain to purchase flood insurance.

[11] Elevate Mandate requires homeowners whose properties located in the floodplain to elevate their homes.

[12] Voucher allows homeowners whose properties located in 'A' or 'V' flood zones to receive discounts on their premiums (Kousky & Kunreuther 2013)

[13] Subsidized Disaster Loan from the U.S. Small Business Administration.

6	yes	yes	no	yes	no
7	yes	yes	no	no	yes
8	yes	yes	no	no	no
9	yes	no	yes	yes	yes
10	yes	no	yes	yes	no
11	yes	no	yes	no	yes
12	yes	no	yes	no	no
13	yes	no	no	yes	yes
14	yes	no	no	yes	no
15	yes	no	no	no	yes
16	yes	no	no	no	no
17	no	yes	yes	yes	yes
18	no	yes	yes	yes	no
19	no	yes	yes	no	yes
20	no	yes	yes	no	no
21	no	yes	no	yes	yes
22	no	yes	no	yes	no
23	no	yes	no	no	yes
24	no	yes	no	no	no
25	no	no	yes	yes	yes
26	no	no	yes	yes	no
27	no	no	yes	no	yes
28	no	no	yes	no	no
29	no	no	no	yes	yes
30	no	no	no	yes	no
31	no	no	no	no	yes
32	no	no	no	no	no

Highlands, NJ Scenario (Scenario 19)

"Flood Insurance Mandate, Elevate Mandate, Disaster Loans" represents Highlands, NJ, in which high flood insurance premiums is expected along with low flood risks reduction efforts. High in property prices are also expected from the outputs of these simulation experiments. This scenario is used for calibrating the model.

Union Beach, NJ Scenario (Scenarios 1-4)

"Community Rating System, Flood Insurance Mandate, Elevate Mandate, Voucher (optional), Disaster Loans (optional)" scenario represents Union Beach, NJ, which participates in the CRS program. Therefore, the outputs from the simulation experiments are expected to show high in flood risk reduction efforts among the stakeholders and low in the premiums since the premium discount policy applies. Property prices are expected to be low in the scenario. This scenario is used for validating the model.

5.5. Outputs of Validation Runs

Following a more systematic simulation modeling experimentation as the model developed from simple sub-models into an integrated ABM model, the difference in the simulation run times is immediately detected. Simple models have relatively shorter run time than those created with a complex modeling logic. High variance in the results is also noticeable from running several replicates of sub-models with the same parameter settings. This is because the models are not fully calibrated with data, but instead use stochastic variables. A data-driven ABM model shows more consistencies in the results. Nevertheless, the simulation outputs show that all of the models follow the logic they are developed for.

Figure 5.8 illustrates that the model performs well in predicting realistic trends in the property prices for both towns for the period 2010-2016. Prices for real properties in Highlands are relatively higher than those in Union Beach as indicated by the solid lines. The model outputs follow similar trends as indicated by the dotted lines. Figure 5.8 also shows the model performance in terms of how property prices respond to Hurricane Irene and Hurricane Sandy in 2011 and 2012, respectively. Temporary price drops are seen during these periods before they recover in the following year.

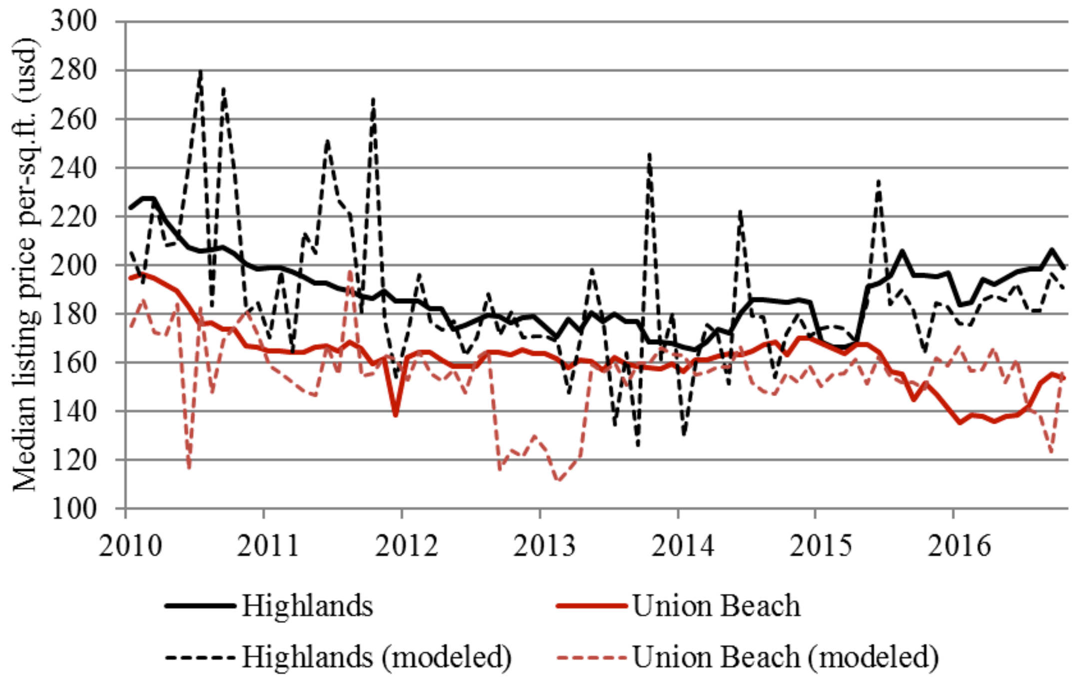


Figure 5.8: A comparison of modeling outputs in terms of property prices for both municipalities

The modeling outputs on flood insurance also follow similar trends as illustrated in Figure 5.9. In 2012, the total amount of claims exceeded the amount of premiums as suggested by both actual data and model outputs for both Highlands and Union Beach. The model, however, performs better as shown in a stable increase in the amount of premiums over the years. This is probably because of a low dropout rate for flood insurance policyholders. The likelihood for policyholders to keep their flood insurance depends on many factors, flood risk awareness is one of them. Findings from Chapter 4 indicate that homeowners, who are well-informed by the FEMA floodplain maps, will likely purchase flood insurance policy. It is also common for property owners to purchase flood insurance after the recent occurrence of floods, especially after their homes were directly affected by the flood. In other words, purchasing flood insurance is also considered as one of the many homeowner's adaptive behaviors to flooding.

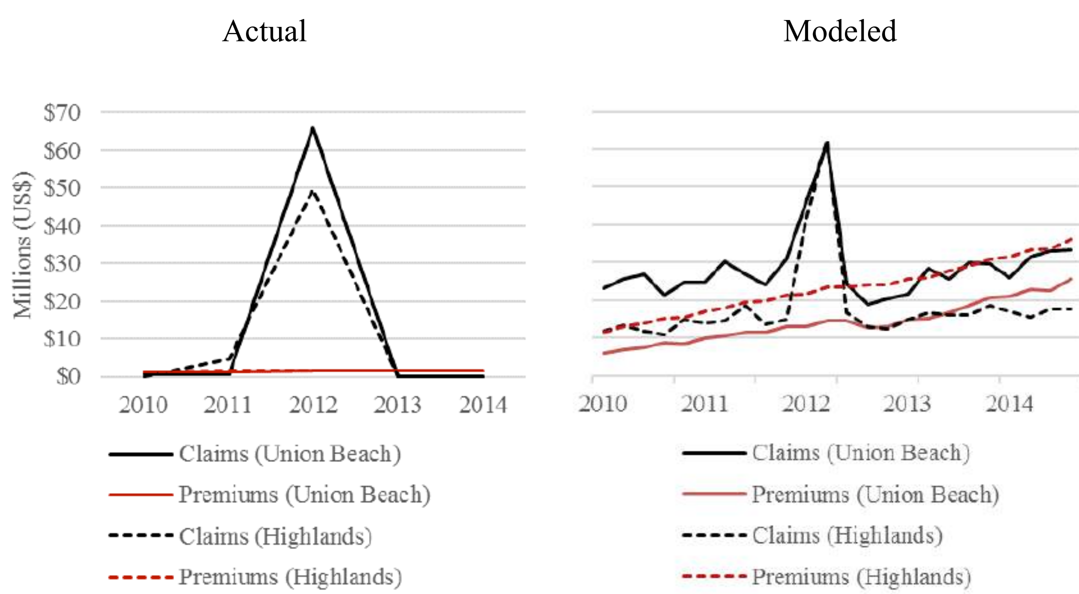


Figure 5.9: A comparison of actual and modeling outputs in terms of collected premiums and total payouts for both municipalities

Figure 5.9 illustrates that the modeling work also considers other adaptive behaviors such as foresight of future flooding risks, participation in (and, satisfaction with) the community recovery efforts after the flooding, evacuation during the flooding, structural raising and repair. By calibrating against survey data, the modeling outputs show that the community of Union Beach, New Jersey adapts better to the recent floods than those in Highlands, New Jersey. This accords with the participation of Union Beach in the National Flood Insurance Program (NFIP)'s Community Rating System (CRS), in which the main components include public information, mapping regulation, damage reduction, and preparedness.

The data used for calibration was from a series of survey activities conducted by the Monmouth University Polling Institute in 2013 and 2014 to the residents in Monmouth County, who were affected by Hurricane Sandy. As illustrated in Figure 5.10, the modeling outputs show that the community in Union Beach has a greater foresight of future flooding risks, which is close to the resulting survey, than those in Highlands. The community in Union Beach is satisfied with the recovery efforts more than those in Highlands. Both communities engage in the recovery efforts in the aftermath of flooding, which is similar to what the survey data indicates. The proportion of evacuees in both communities are also relatively similar. With the elevation requirement for the floodplain properties in Union Beach, more residents in the community raise their properties than those in Highlands. The survey data also indicates a similar result of homeowners raising their properties after Sandy. In terms of the number of repairing the property as one of flooding adaptive strategies, more damaged properties are repaired in Highlands than those in Union Beach. Survey data on repair strategy, however, is not available for calibration.

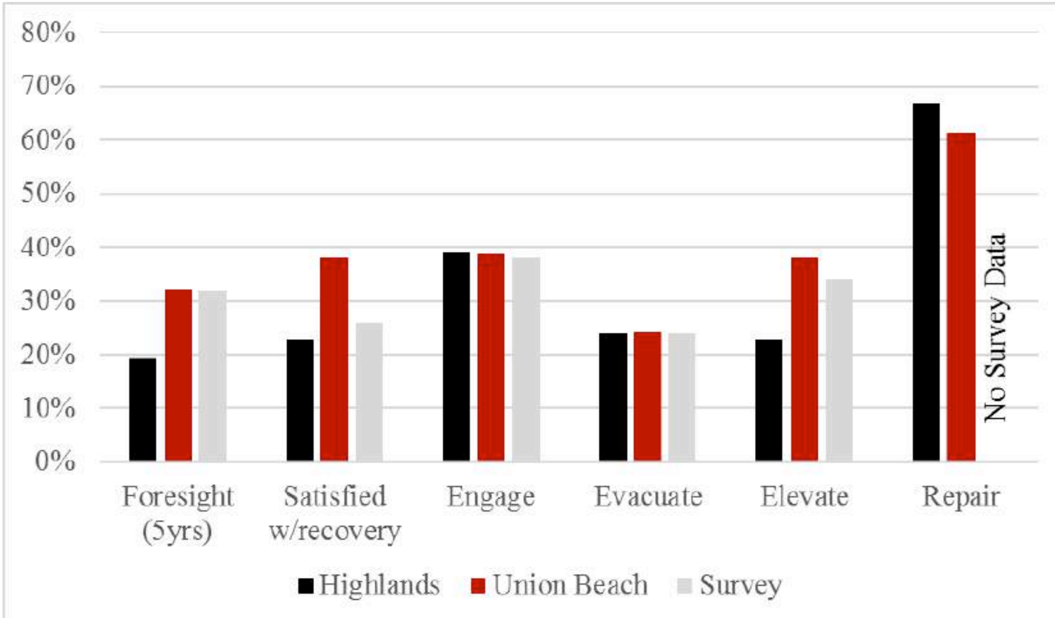


Figure 5.10: A comparison of modeling outputs for adaptive behavior toward coastal flooding for both municipalities

5.6. What-if Scenario Outputs

Flood return period influences flood risk, which is capitalized in the real property price as suggested in Figure 5.11. In a scenario, where Highlands was hit by a 100-year flood for every 5 years, the modeling output shows a slow increase in the property transaction price. On the other hand, a faster increase on the projected property transaction price is observed when a 100-year flood hit the town at a longer return period (10-year return period). Similar trends are also shown in the simulation scenario by using Union Beach.

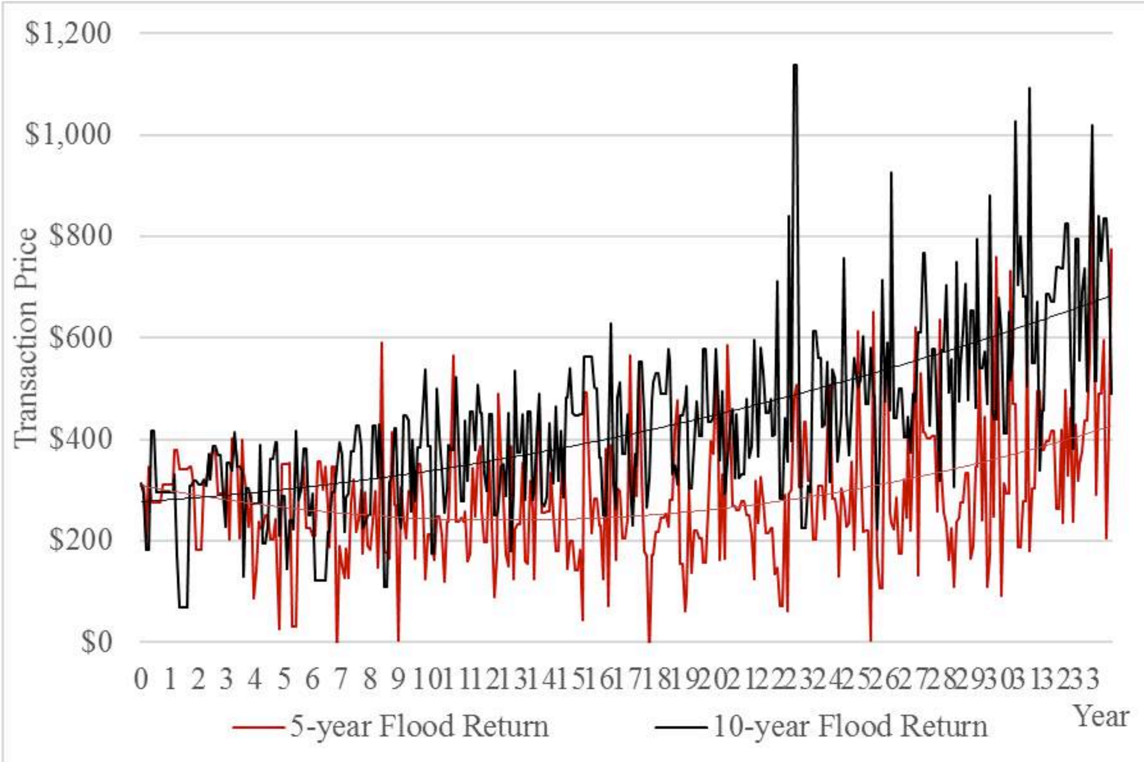


Figure 5.11: Modeling outputs on transaction prices under two different flood return periods

Price drops in a real property market after flooding are also an indicator of urban disinvestment. Another indicator is population decline. Figure 5.12 illustrates an output of the modeling experiment to explore the third hypothesis of whether there is a correlation between flooding and the number of homeowners selling their properties because of leaving the town. It is noticed that sales jump in just three months after flooding and start to recover to the trends before the flooding.

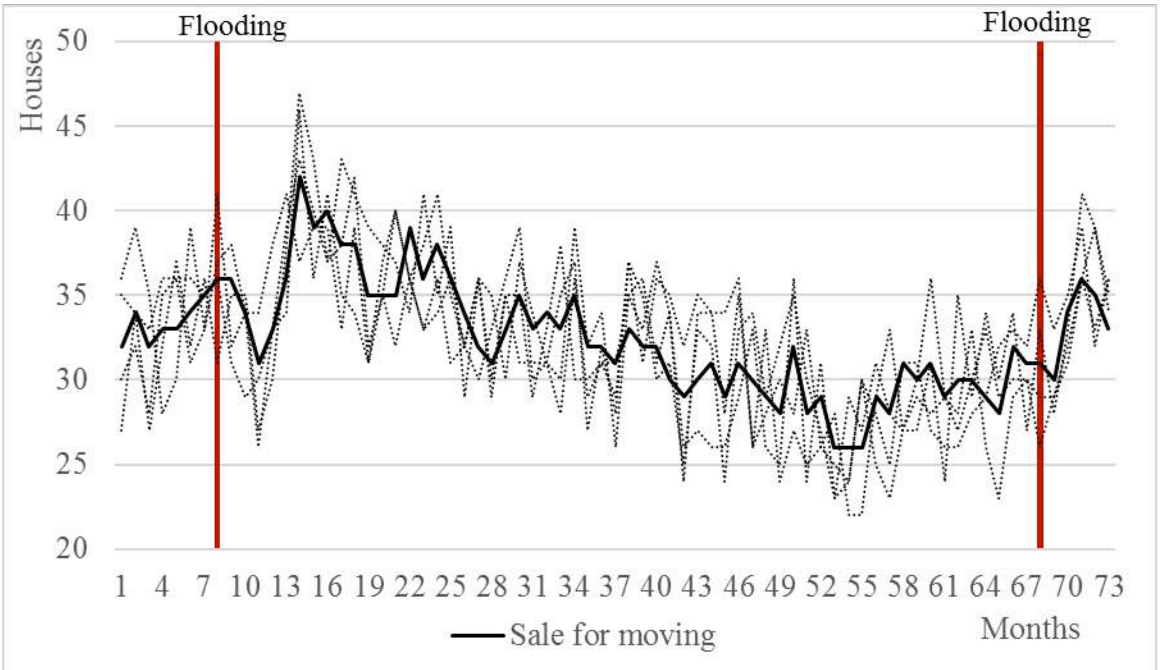


Figure 5.12: Modeling outputs on the number of houses for sale for moving reason

Figure 5.13 illustrates the modeling output of whether the effects of flooding on CRS communities are different from those on non-CRS communities. There are four evaluation categories on community actions in the FEMA Community Rating System (CRS). Communities enter the program by implementing flood reduction efforts, which are evaluated based on the availability of public information, mapping and regulations, flood damage reduction, and flood preparedness. CRS participating communities are eligible for discounts up to 45 percent in the flood insurance premium. Homeowners residing in the CRS communities are assumed to have better foresight on flood risk. Less in damages caused by flooding are also expected on these owners' properties. Though their properties are insured, thereby, fewer amounts of payouts are burdened to the flood insurance program. Figure 5.12 shows a superior performance by CRS communities in both modeling outputs for the number of homeowners with foresight of flood risk and the amount of flooding payouts.

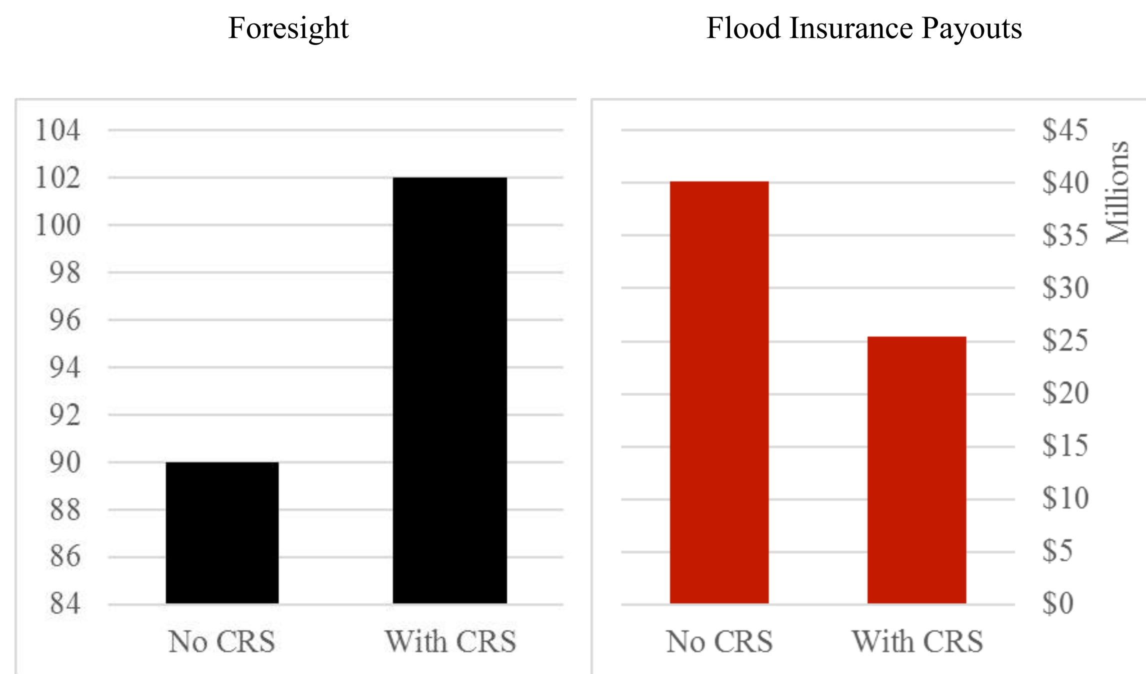


Figure 5.13: Modeling outputs for stakeholders' foresight of future flood risk and flood insurance payouts given the CRS participation

5.7. Conclusions

Resilience in planning practice relies on an understanding of socio-economic and ecological systems and in the analysis of the interacting systems and their vulnerabilities. This chapter suggests that resilience has shifted the planning approach from a top-down view and a desire to control the change resulting from the interactions, to focus on the capacity of the systems to adapt to the change. Resilience concepts that systematically link physical (spatial) and ecological aspects have invited researchers to develop models that are able to deal with both changes and behavioral responses to the changes. One important pre-requisite for any modeling effort is to present just enough complexity to suggest reality but no more, in which the components include spatial landscape and interacting actor-agents.

Agent-based models (ABMs) have promising features that this dissertation finds useful in the analysis of complex phenomena, particularly coastal flooding. Despite its limitations, our ABM model successfully serves the motivation to explore coastal flooding and stakeholder responses. The ABM model uses an explicit GIS maps to provide a realistic representation of the spatial environment. In addition to decision mechanisms embedded within the model, the ABM model also co-simulates with hedonic pricing model to mimic price estimation behavior of the real property developers.

The calibration and validation simulation runs suggest that the proposed ABM model well-represents real property markets in both Highlands and Union Beach. Insights from running the simulation scenarios suggest several points related to public policy. First, any flood-risk reduction effort such as elevating the property's structure lowers the amount of claims in the aftermath of flooding. Another policy impact related to financing flood insurance is the premium discount programs such as the FEMA CRS program and and voucher provision (Kousky & Kunreuther 2013) as two of the many modes to increase the flood insurance penetration rates in communities. The modeling outputs also suggest the importance of information dissemination (one of the CRS components) in increasing the people's awareness of flood risk. Further, the outputs suggest that the sales occurred after Sandy were due to foreclosures or buyouts or homeowners leaving the community. In other words, large flood events like Hurricane Sandy may lead to urban disinvestment and population decline as suggested by the third hypotheses.

Chapter 6

Conclusions

6.1. Summary of Findings

This dissertation produces findings that accord with the five hypotheses mentioned in the first chapter. Chapter 3 discusses and tests the first hypothesis “Real property markets fully capitalize flood risk into the prices of properties”. The resulting analyses suggest that floodplain properties are low in price compared to their counterparts located outside the floodplain. Similar results are also seen in the prices for properties that were affected by Sandy and in close proximity to the coast. There is also a correlation between housing tenureship and property price. Hurricane Sandy had more effects on owner-occupied properties than absentee-owner properties.

Chapter 3 also discusses the likelihood of homebuyers to consider flood risk when buying properties, as suggested in the second hypothesis. The findings from the analyses show that the property prices dropped immediately after Sandy. This may be due to buyers taking account of recent floods to inform their awareness of flood risk; hence, bidding for a desired property at a lower price is a reasonable response. Chapter 5 explains in detail about the behavior of homebuyers and other stakeholders in regards to property price estimation. The agent-based modeling outputs suggest that the less the real property price capitalizes flood risk, urban disinvestment and population decline may as well be avoided as suggested by the third hypothesis. Chapter 5 also tests the fifth hypothesis, “Community-level risk reduction efforts vary across municipalities and it influences stakeholders' perception on future risks and the actual impact of flooding". The modeling outputs show that any community-level effort to reduce flood risks is mainly driven by the government's effort. Although a 'contagion' feature is enabled in the simulation experiment to allow homeowner-agents to influence each other behaviors, yet, there is only a small effect. The government's decisions tend to overpower the homeowners' decisions as in the example where the government's mandate for floodplain property owners to elevate their properties' structures. Another example is the discount programs that incentivize property-owners to invest in the flood insurance.

Flood insurance is also considered as a flood-risk reduction effort. Findings from Chapter 4, which investigates the patterns of flood insurance purchase in Monmouth County, accords with the hypothesis "National Flood Insurance Program (NFIP) has the unanticipated consequence of moral hazard to encourage development in flood risk areas". When Hurricane Irene and Hurricane Sandy hit Monmouth County, New Jersey in 2011 and 2012, respectively, the amount paid out in flood insurance claims exceeded the expected claims amount calculated through the premiums collected from the policyholders. This shows that flood insurance markets as well as communities were not well prepared in anticipating large-scale storms like hurricanes. Municipalities with large floodplain areas tend to have large number of flood insurance policyholders. The resulting analysis shows that FEMA floodplain maps inform floodplain property owners and persuade them to purchase flood insurance. In terms of the amount of payouts after flooding, absentee-owner properties have higher payouts caused by flooding, although they have lower policy take up rates, than those that are owner-occupied. Post-FIRM properties, as expected, are lower in the total payouts.

6.2. Contributions

This dissertation contributes to the literature in several ways. The first theoretical framework is on the discourse of three major urban planning paradigms, namely rational comprehensive planning, communicative planning, and resilience planning. The dissertation adopts a resilience planning paradigm by investigating natural-social phenomena and their complexity. In the planning world, these phenomena commonly interact with the economics, particularly, with the land as one of the economic resources. In international agricultural economics, as for example, land determines the power and relation of nation-traders participating based on their political and economic interests manifesting in the roles. The next accounted theory is the economic agents that are involved in the complex interaction. These agents act either individually or collectively by forming institutions. In this dissertation, these theoretical discourses are discussed in the context of coastal flooding and the real property and flood insurance markets.

Further within the resilience literature, this dissertation demonstrates the value of using various analytical tools in understanding urban planning issues and their complexities. The traditional OLS regression, fixed effects, and the spatial hedonic pricing model are some of the many mathematical models that utilize empirical data to identify the issues. In using these tools, the more exhaustive the amount of data, the more optimal solutions the analysis would produce. The calibrated ABM model proposed in the dissertation enable us to do a walk-through of the agents' decision processes and emergences. The ABM models are a means to explore decision mechanisms that occur within urban actors, decisions related to coastal flooding adaptation, as for example (see Chapter 5). Thereby, the modeling outputs are not only useful for identifying urban issues, but are also helpful for policy communication.

Some policy implications of the outcomes of this dissertation may include aspects varied from stakeholder behavior to climate resilience policies. The hedonic property pricing models described in Chapter 3 allow property appraisers to explore the components of flood risk capitalized into the property prices. The resulting historical analysis also enables appraisers to track any 'surprises' on the prices caused by flood events. The resulting analysis on flood insurance market penetration and flooding payouts as discussed in Chapter 4 provides a larger picture of the dynamics of flood insurance markets from both the revenue and cost sides by identifying the determinants of flood insurance purchases and payout claims. This will be especially relevant in reforming the financing of the National Flood Insurance Program (NFIP), which now is in great debt. Insurance companies may as well be able to anticipate future disasters without fear of being strained their resources, hence, underpay the impacted policyholders. These mathematical/econometrics models provide confidence due to the availability of exhaustive data.

Linking the above data-driven models to the behaviors of stakeholders participating in coastal real property markets (and flood insurance markets) requires a model that more fully explores the dynamics of these markets. The proposed ABM model discussed in Chapter 5 allows insurers, climate resilience researchers, and town planners to explore several behavioral and organizational elements that will determine the success of coastal flooding resilience efforts. As more options are available for flood insurance policyholders to reduce their premiums, issues of homeowner flood risk awareness and adaptations will increase relatively. This will be relevant to owners, whose properties are located in the floodplain, or not occupying their properties. The confidence in the proposed ABM model is based on the calibration and validation processes against two real towns (or two real property markets) that were impacted by Hurricane Sandy in 2012. Moreover, the proposed model is a more advanced version of Handi's 2015 model due to its integration with the hedonic property pricing model. A more realistic representation of the homeowner adaptive behaviors to future flooding is also driven by household survey responses that were previously conducted by the Monmouth University Polling Institute in 2013 and 2014.

6.3. Limitations and Caveats

Throughout the dissertation process, there are some limitations and caveats that could take part in the future research agenda. Summarizing the issues that were already addressed in the previous chapters, the limitations are mainly surround the data collection and method selection. The first is in regards to accuracy and completeness of data sources, especially MOD IV and SR-1A and FIRM maps. These data are consistently updated to meet the standard of accuracy as the data collection techniques are getting more advanced. The logical issues in some of the analytical and ABM models are also potentials for future improvement. For example, the proposed models do not deal with real properties that were destroyed and lost their land (or under water) due to flooding caused by Hurricane Sandy. Another example is in the selection of nearest distance calculation methods that are varied depending on the types of amenities. Euclidian distance maybe appropriate for calculating distance to the nearest coastlines but not to schools or transit hubs. Network distance is more logical to serve these kinds of calculations. The ABM model can also incorporate more realistic components, such as having a developer role separate from an appraiser role, instead of having a single modeled agent to represent both roles. Additional analyses that are relevant to the overall discussion should be included. They include, as for example, Sandy's impacts on real properties that have been sold for multiple times and the homeowners' learning behaviors from repetitive flooding.

6.4. Future Research

Therefore, it is reasonable to frame a future research agenda with priorities such that the above limitations and caveats will be resolved. Along the same lines, other research priorities include the calibration of the proposed ABM model to different towns, countries, and real property markets. More on the technical standpoint, the proposed ABM model can be made ready as a communication tool for planners by incorporating a more user-friendly visualization and more realistic policy-scenario simulations. Moreover, the advancement of computing power and programming algorithms, the model can be enriched with additional stakeholders' decision mechanisms to better reflect human economic decisions.

Appendix A

Data and Sources

Variables and Sources

Variables	**Description**	**Data Sources**
SALEPRICE (usd)	Sales price in 2015 US dollars. Log-transformed for the analyses. Property level	Monmouth County Tax Board SR-1A
BLACKPCT (%)	Percent of African American population. Block group level	US. Census. ACS 2010 – year
COLLEGEPCT (%)	Percent of population with college degree. Block group level	US. Census. ACS 2010 - year
RENTTOTAL (usd)	Total rent. Block group level	US. Census. ACS 2010 - year
MEDINCOME (usd)	Median household income. Block group level	US. Census. ACS 2010 - year
HHSIZETOTAL	Total of household size. Block group level	US. Census. ACS 2010 - year
VACANTPCT (%)	Percent of vacant homes. Block group level	US. Census. ACS 2010 - year
COAST (=1)	A dummy var. indicates adjacent to coastline	
OWNEROCCUPIED (=1)	A dummy var. indicates property location is the same as buyer mailing address	SR-1A columns “Grantee’s Mailing Address” and “Property Location”
SEWER (=1)	A dummy var. for availability of sewer connection	Monmouth County Tax Board MOD-IV column “SEWER”
WATER (=1)	A dummy var. for availability of	MOD-IV column

	water connection	"WATER"
GAS (=1)	A dummy var. for availability of sewer connection	MOD-IV column "GAS"
SEPTIC (=1)	A dummy var. for availability of septic connection	MOD-IV column "SEPTIC"
BLDGAGE (years)	A variable for the property age, calculated by subtracting the column "year built" from 2016	MOD-IV column "year built"
SQFT (square feet)	A dummy variable for property size in square feet	MOD-IV column "sq.ft"
CONDITION (=1)	A dummy var. for the building condition	MOD-IV column "condition"
ROOMS	A variable for a number of rooms	MOD-IV column "num.of rooms"
HEIGHT	A variable for a building height	MOD-IV column "height"
FCONCBLK (=1)	A dummy var. for a structural foundation type of concrete block	MOD-IV column "foundation"
FCONCSLB (=1)	A dummy var. for a structural foundation type of concrete slab	MOD-IV column "foundation"
FCONCPOUR (=1)	A dummy var. for a structural foundation type of concrete pour	MOD-IV column "foundation"
FPIERPIL (=1)	A dummy var. for a structural foundation type of pier pil	MOD-IV column "foundation"
FSTNBRK (=1)	A dummy var. for a structural foundation type of stone brick	MOD-IV column "foundation"
hasAC (=1)	A dummy var. for an availability of an air-conditioning system	MOD-IV column "AC"
hasFIREPLACE (=1)	A dummy var. for an availability of a fireplace	MOD-IV column "Fireplace"
hasDORMER (=1)	A dummy var. for an availability of a dormer	MOD-IV column "Dormer"
hasDECK (=1)	A dummy var. for an availability of a deck	MOD-IV column "Deck"

hasDOCK (=1)	A dummy var. for an availability of a dock	MOD-IV column "Dock"
hasPOOL (=1)	A dummy var. for an availability of a swimming pool	MOD-IV column "Pool"
hasSHED1STY (=1)	A dummy var. for an availability of a one-story shed	MOD-IV column "shed1sty"
hasBRICK (=1)	A dummy var. for a structural attribute of brick	MOD-IV column "brick"
POSTFIRM (=1)	A dummy var. for a property built after 1974 (or after FIRM)	MOD-IV column "year built"
CoastDIST (feet)	An Euclidian distance to the nearest coast line. Log-transformed for the analyses.	MOD-IV and NJDEP Coastline 2012
StreamDIST (feet)	An Euclidian distance to the nearest stream. Log-transformed for the analyses.	MOD-IV and NJDEP
RailStDIST (feet)	An Euclidian distance to the nearest rail station. Log-transformed for the analyses.	MOD-IV and NJGIN
PoliceDIST (feet)	An Euclidian distance to the nearest police station. Log-transformed for the analyses.	MOD-IV and NJGIN
PollutDIST (feet)	An Euclidian distance to the nearest contaminated sites. Log-transformed for the analyses.	MOD-IV and NJDEP
SchoolDIST (feet)	An Euclidian distance to the nearest school. Log-transformed for the analyses.	MOD-IV and NJGIN
FLDZONEA (=1)	A dummy variable for flood zone A zone	MOD-IV and FEMA Map Service
FLDZONEV (=1)	A dummy variable for flood zone V zone	MOD-IV and FEMA Map Service
FLDZONEX500 (=1)	A dummy variable for flood zone X500	MOD-IV and FEMA Map Service
FLDZONEX (=1)	A dummy variable for flood zone	MOD-IV and FEMA Map

	Z	Service
COAST500 (=1)	A dummy variable for distance within 500 feet to the nearest coastline	MOD-IV and NJDEP
COAST1000 (=1)	A dummy variable for distance between 501 and 1,00 feet to the nearest coastline	MOD-IV and NJDEP
COAST2000 (=1)	A dummy variable for distance between 1,001 and 2,000 feet to the nearest coastline	MOD-IV and NJDEP
COAST3000 (=1)	A dummy variable for distance between 2,001 and 3,000 feet to the nearest coastline	MOD-IV and NJDEP
COAST4000 (=1)	A dummy variable for distance between 3,001 and 4,000 feet to the nearest coastline	MOD-IV and NJDEP
COAST5000 (=1)	A dummy variable for distance between 4,001 and 5,000 feet to the nearest coastline	MOD-IV and NJDEP
ASANDY (=1)	A dummy variable for sales after Sandy	MOD-IV
ASANDY1M (=1)	A dummy variable for sales within a month after Sandy	MOD-IV
ASANDY2M (=1)	A dummy variable for sales in December 2012	MOD-IV
ASANDY3M (=1)	A dummy variable for sales in January 2013	MOD-IV
ASANDY4M (=1)	A dummy variable for sales in February 2013	MOD-IV
ASANDY5M (=1)	A dummy variable for sales in March 2013	MOD-IV
INUNDATED (=1)	A dummy variable for inundation	MOD-IV

FEMA Flood Zones

VE zone	An area inundated by 1% annual chance flooding with velocity hazard (wave action); BFEs have been determined.
A zone	An area inundated by 1% annual chance flooding, for which no BFEs have been determined.
AE zone	An area inundated by 1% annual chance flooding, for which BFEs have been determined.
X500 zone	An area inundated by 0.2% annual chance flooding; an area inundated by 1% annual chance flooding with average depths of less than 1 foot or with drainage areas less than 1 square mile; and areas protected by levees from 1% annual chance flooding.
X zone	Areas determined to be outside 500-year floodplain determined to be outside the 1% and 0.2% annual chance floodplains.
D zone	An area of undetermined but possible flood hazards.
BFE	Base Flood Elevation (BFE) is the computed elevation to which floodwater is anticipated to rise during the base flood. The BFE is the regulatory requirement for the elevation or floodproofing of structures. The relationship between the BFE and a structure's elevation determines the flood insurance premium.

Data Source: FEMA Flood Zones https://www.fema.gov/flood-zones

Appendix B

ODD Protocol

In this protocol the ABM model on real estate market stakeholders' responses to coastal flooding will be described using the ODD protocol standard. The ODD Protocol, developed by Grimm et al. (2006), is used to standardize the published descriptions of individual-based and agent-based models (ABMs). The ODD protocol has three categories as it stands for Overview, Design concepts, and Details. The overview category provides the overall purpose and structure of the model, with which readers get an idea about the entities and state variables included in the model, as well as the spatial and temporal scales and extents. The second category, design concepts, describes the general concepts of the model's design. In the Details category, there are three components that include initialization, input data, and sub-models; that provide technical details of the model. Table 1 provides an overview of the different components of the ODD protocol.

Table B.1: ODD Protocol (Grimm et al., 2010)

Categories	**Components**		
Overview	1. Purpose 2. Entities, state variables, and scales 3. Process overview and scheduling		
Design concepts	• Basic principles • Emergence • Adaptation • Objectives	• Learning • Prediction • Sensing • Interaction	• Stochasticity • Collectives • Observation
Details	1. Initialization	2. Input data	3. Sub-models

2.1. Purpose

The overarching purpose of the modeling study is to identify internally consistent and plausible narratives on the market stakeholder behavioral patterns in the coastal real estate market under large flood events. This is achieved by means of an exploratory modeling approach to the development of what-if scenarios in which the emergence of adaptation action from the individual decisions and interactions of heterogeneous economic agents in the dynamics of real property markets. Moreover, it also explores the uncertainties and its consequences influencing the emergence of coastal flooding adaptations.

2.2. Entities, state variables, and scales

The section describes the agents in the model, by defining the state variables and attributes that characterize these agents. The section also elaborates n the temporal and spatial resolutions and extents of the model.

2.2.1. Agents/Individuals. The model has different types of agents

- Houses are physical structures located within the parcel boundaries. There is only a single house within each parcel. Houses have the following attributes, which some overlap with parcel attributes:

Variable	Description	Variable	Description
hPatch	Which patch	pfloodZone	Flood zone
pBasement	Has basement	pSewer	Has sewer
pWater	Has water	pGas	Has gas
pSeptic	Has septic	pRooms	# of rooms
pHeight	# of floods	pAC	Has A/C
pDormer	Has dormer	pDeck	Has deck
pDock	Has dock	pPool	Has pool

pSqft	Square feet	pPOSTFOR<	Pos FIRM
pCoastDist	Distance to coast	pStreamDist	Distance to stream
oBusStopDist	Distance to bus stop	pRailStDist	Dist. to rail station
pPollutDist	Dist. to pollution	pSchoolDist	Dist. to school
pBlack	% black pop	pCollege	% Coll. Graduates
pPop25	% 25 and above		
hforSale	T if for sale	hforRent	T if for rent
hneighborList	List of neighbor houses	hisInfluence	Decision contagion
Hdownpayment	Downpayment	hmortgagePmt	Mortgage
hmaintenancePmt	Maintenance fees	hElevatePmt	Elevation fee
hrecentFloods	# floods in the last 2 yrs	hisFloodInsured	Is house insured?
hfiPremium	Insurance premium	hfiCoverage	Covered
hisElevated	Is house elevated?	hbldgAge	#years
hrentPrice	Rental price	hhouseValue	House value
hisFlooded	Is house flooded	hfloodDamage	% of house damaged
hfloodLoss	$ value of losses	hfiClaim	Insurance payouts
hfloodRepairPmt	Repair payment	hSBALoan	Disaster loans

- Households are categorized into two different types: homeowner/home seller and home buyer. Each owner-occupied house owned only by a single household. Whenever the homeowner puts the home for sale, he or she becomes home seller and home buyers may bid for the home. Households have the following attributes:

Variable	**Description**	**Variable**	**Description**
ohouse	Occupied house	obestHouse	Best house found
orole	Homeowner, homebuyer	oincome	
odpratio	% income for downpayment	omortgageratio	%income for mortgage
ohousingRatio	%income for housing	oenterTime	Tick enter the model
otenureTime	# ticks in certain role	osellTime	# ticks as a seller
oisTraded	Traded in market	tradeWith	Other transaction

			party
obidPrice	Bid for buyer	oaskPrice	Ask for seller
oconsiderFlood Risk	T if aware of flood risk	Oconsider Waterfront	T if desire for waterfront props.
oconsiderCBD	T if want CBD area		

- Bank is an agent that owns all empty parcels and foreclosed house-agents. Bank has the following attributes:

Variable	**Description**
bAssets	Dollar amount

- Local Government is an agent that manages disaster stimulus and issue approval for development proposals sent by developers. A local Government has attributes as follow:

Variable	**Description**	**Variable**	**Description**
gTaxCollected	USD of tax	gGrants	Amount of grants
gmaxFloodRisk	Govt. regulated flood risk		

- Insurer is an agent that represents insurance company, whose role is to promote flood insurance, to collect premiums, and to pay for claims in the aftermath of flooding. An insurer agent has attributes as follow:

Variable	**Description**	**Variable**	**Description**
nlossRatio	Payouts/premiums	maxlossRatio	Max acceptable loss ratio
nbasePremium	Base premium	nAssets	Amount of assets
nPremiumReceivd		nClaimsPaid	

- Developer agent builds and sells houses. A developer agent has the following attributes:

Variable	Description	Variable	Description
dAssets	Amount of assets	dDemandList	Housing in demand
dLand	Patches for development	dproposedLot	Lot to propose to build a house
dproposedFlood Risk	Acceptable flood risk	disapproved	T if proposal is approved by govt.

2.2.2. Environment

- Environmental variables: time series data of flood level, FEMA floodplain maps, distance to closest amenities.
- Economic variables: property market price, insurance premium, mortgage fee, repair fee, structural elevation fee, maintenance fee, flood loss, rental price, mortgage interest rate, mortgage term, property tax rate, income tax rate, inflation rate, cash return rate,
- Time variables: Day. One time step represents one day and simulations were run within 5 year period (2010-2014).
- Collectives: The model has six agentsets, collection of agents.

2.2.3. Process overview and scheduling

This section provides an overview of the internal mechanisms of the model using a model narrative and detailed pseudo-code. In the initialization of a model run, the processes are performed by the creation and implementation of the environment and agents' attributes. They are the GIS representation of the case towns, house-agents, owners and sellers ofhouses, a developer, an insurer, and output variables.

```
to setup
```

```
   clear-all
   file-close-all
   reset-ticks
   setupGlobalParameters
   setupGIS
   setupHouses
   setupOwnerSellers
   setupBank
   setupLocalGovernment
   setupDeveloper
   setupInsurer
   setupOutputHeader
end
```

Every tick, which represents a month, the following processes are executed:

1. goHouses – individual houses update the parameters based on parameters from previous processes.
2. goPersons – individual homeowners and sellers update the parameters on waiting schedules and other parameters setting.

```
to go
   reset-timer
   goHouses
   goPersons
   setupBuyersRenters
   goLocalGovernment
   goDeveloper
   goInsurer
   goBank
   goDoubleAuctionMarket
   goFlooding
   tick
   if (ticks >= maxNumberOfTicks)
   [ file-close
      write-output
      stop
   ]
   repeat-go
end
```

2.4. Design concepts

a. Basic principles. The model adopts several sub models related to stakeholders responses in real estate market toward coastal flooding by integrating agent-based model (ABM) and spatial econometrics to explore individual and collective behavior patterns.

b. Emergence. Some of the emergences identified in the model vary from rent vs. own decisions, property and rental prices, flood insurance policies-in-force, and flood risk perceptions and adaptations.

c. Adaptation. Homebuyers evaluate their current asset situation in investing in their desired homes of whether to purchase or to rent. Homeowners adjust flood risk perception based on many factors related to flood risk awareness. Homesellers ask for the developer recommendation from their hedonic pricing estimates to set ask price. Local government decides on the approvals for development proposals.

d. Objectives. Homebuyers' objective is to look for a desired home that fits budget and necessary amenities. Homeowners' objective is to be able to afford to keep the house and adapt against future flood events. A developer's objective is to meet the housing demand, to look and propose for development land, to build flood-resistance homes, and to sell homes at market price. An insurer's objective is to promote flood insurance policy purchase and to mediate between the FEMA national flood insurance program (NFIP) and homeowners. Local government's objective is to make their community aware of flood risk and perform mitigation efforts. Bank's objective is to foreclose houses and maintain unsold houses.

e. Learning. Homebuyers adjust their bid price in the market. Homesellers request for price recommendation from the developer's running hedonic property pricing model. Homeowners and local government adjust their flood risk perceptions.

f. Prediction. Stakeholders adapt based on their capacity to anticipate without a complete accuracy in predicting future flood events affecting the real property market dynamics. The timing for the stakeholders to make actions describes the capacity to predict the perceived future.

g. Sensing. Stakeholders rely on their evaluation of previous and current states within the real property market to perceive about their immediate future states.

h. Interaction. Homebuyers-agents compete with each other in the real property market that is processed through the double auction market mechanism. Homesellers-agents interact with the developer for ask price recommendation. A developer-agent interacts with the local government to get building permits. An insurer-agent mediate the relationship between government and homeowners in the flood insurance market.

i. Stochasticity. Neighborhood effects (neighbors contagion) are measured stochastically.

j. Collectives. The two housing markets are based on two coastal towns in Monmouth County, New Jersey, namely Union Beach and Highlands. Sets of agents interact with each other based on the types of interactions such as in the market transaction and flooding adaptive strategies.

k. Observation. Data is collected from multiple different sources that include environmental data, neighborhood data, property data, sales data, and behavior data.

2.5. Input data.

The model uses multiple inputs for calibration and validation purposes.

2.6. Sub-models

Each time tick represents one day. Each day, the behavior model runs the following main sub-processes.

a. Flooding and flood impacts: Determine the water level and flood level on properties. Determine the percentage of flood damages on property values.

b. BuyerRenters: Determine to either purchase or rent a real property.

c. DoubleAuctionMarket: Determine a transaction of a house whenever an ask price meets a bid price.

d. PriceEstimates: Determine the valuation of a property price by running a hedonic property pricing function.

e. FloodInsurancePurchase: Determine the premium rates, coverages, and discounts apply to any potential policy holder.

f. FloodRiskAdjustment: Determine the minimum flood risk measures.

g. NeighborsEffect: Determine the level of influence among homeowners in performing the adaptation strategies.

h. Calibration and validation: Use spatial data and other real data on two towns, namely Union Beach and Highlands, New Jersey, to calibrate and validate the model.

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